

Improving Performance of Open Access Clinics

Tian Xia

MSc in Management Program

**Submitted in partial fulfillment
of the requirement for the degree of**

**Master of Science in Management
(Operations and Information Systems Management)**

Goodman School of Business, Brock University

St. Catharines, Ontario

©2014

To Mom and Dad,
who always picked me up on time
and encouraged me to go on every adventure,
especially this one

Abstract

Open Access Scheduling has shown great promise in allowing health care practices to provide same-day access, and to match patients with their regular physicians. However, similarly to traditional clinics where appointments are pre-booked, open access clinics are also frustrated with long waits, long idle time and long overtime due to uncertainties such as patient no-shows, variable service time and variable daily demand. These aspects have not been studied previously in an open access setting. This study investigates different management options to improve clinical performance in terms of patient waiting time, doctor idle time and clinic overtime. Other factors studied with a simulation model include client load and placement of pre-booked slots. Results show that a proper panel size is critical to obtain good performance for open access clinics, and that good choices for management options depend on the client load.

Keywords: simulation, open access scheduling, service operations

Acknowledgements

There are a number of people without whom this thesis might not have been written, and to whom I am greatly indebted.

I would like to thank my supervisor, Dr. Ken Klassen, for the patient guidance, encouragement and advice he has provided throughout my time as his student. I have been extremely lucky to have a supervisor who cared so much about my work, and who responded to my questions and queries so promptly.

I would also like to thank my supervisory committees, Dr. Martin Kusy and Dr. Reena Yoogalingam, for the very useful suggestions they made to this study.

Finally, I would like to thank all my friends and all those who have played important roles in my life for their continued support and encouragement.

Table of Contents

1. Introduction	1
2. Literature Review	3
2.1 Open Access Scheduling Implementation.....	3
2.2 Appointment Lead-Time	9
2.3 Continuity of Care	13
2.4 No-show Rates.....	17
2.5 Patient Visits	18
2.6 Balance Demand and Capacity	19
2.7 Patient Waiting Time, Doctor Idle Time and Clinic Overtime.....	21
3. Gaps and Contribution	23
4. Research Model	25
4.1 Interview Findings.....	25
4.2 Simulation Model	26
4.3 Factors Tested	30
4.3.1 Client Load	30
4.3.2 Management Options.....	30
4.3.3 Pre-booked Slots Placement	32
4.4 Performance Measurement.....	33
5. Research Methodology	35
6. Results and Discussion	38
6.1 Client Load	40

6.2 Management Options.....	42
6.3 Pre-booked Slots Placement	46
6.4 CL*MO	47
6.5 CL*PSP	49
6.6 MO*PSP	51
6.7 CL*MO*PSP	52
7. Conclusions and Managerial Implications	55
8. Limitations and Future Research	57
References	59
Appendix	62

1. Introduction

Open Access Scheduling, also known as the “Second Generation Open Access System”, was introduced by Murray and Tantau in 1999 to help clinics reduce appointment lead-time and improve accessibility. This system allows patients to book appointments with their regular physicians on the same day when they call regardless of their medical issues. The goal of this study is to help open access clinics reduce patient waiting time, doctor idle time and clinic overtime.

The importance of reducing patient waiting time, doctor idle time and clinic overtime has been studied in previous literature. A long waiting time can be extremely annoying to patients. In fact, waiting time has been increasingly used by patients to choose health care providers (Gopalakrishna and Mummalaneni 1993). It has become increasingly important to health care providers to reduce patient waiting time in the clinic and to reduce doctor idle time and clinic overtime as it is an important component of providing high quality health care at a low cost and to improve patient and staff satisfaction.

Researchers and practitioners have been trying to reduce patient waiting time, doctor idle time and clinic overtime. However, their efforts do not always pay off due to the complex nature of appointment scheduling. It is well known that in traditional clinics these issues are results of uncertainties such as random patient arrivals and doctor service time. Similarly to the traditional clinics, open access clinics are also frustrated with these issues due to uncertainties. In addition, variable daily demand and different characteristics between pre-booked patients and open access patients in terms of no-show rates also add to the uncertainties, which has made open access

clinics even more complex to administer than traditional clinics. The existence of long waiting time, long idle time and long clinic overtime has also been confirmed by an interview and data collection at an open access clinic in Hamilton, Ontario.

Case study is the most commonly used method to address issues with open access scheduling, including how to implement an open access scheduling system, how to balance the demand and capacity and the effect of open access scheduling on appointment lead-time, continuity of care, patient no-shows and patient visits. Kopach (2007) used simulation modelling to examine the effect of open access scheduling on continuity of care and clinic throughput. The most recent studies have used analytical methods to improve performance of open access clinics; however, many questions still remain unresolved. One open question is how to minimize patient waiting time in an open access clinic with different levels of demand (client load, which is determined by panel size). Another unresolved issue is where to place the pre-booked slots during the day. Finally, although previous studies have tested a number of scheduling rules (management options) in traditional clinics, little has been done with open access clinics. This study will focus on these issues to improve the performance of open access clinics. In contrast to open access research, the most commonly used methods in traditional outpatient appointment scheduling studies are simulation modeling and analytical methods. This study will use simulation modeling to study open access systems.

The rest of this study will proceed with a comprehensive literature review. Following that, gaps are identified and contributions of the study are presented. After that, the research model and the methodology are explained. Then, the result analysis

and managerial implications are provided. Finally, the limitations of this study and future research guidance are outlined.

2. Literature Review

2.1 Open Access Scheduling Implementation

Murray and Tantau (1999) first introduced the Second Generation Open Access System, which was called “open access scheduling” more often by researchers and practitioners later on. They introduced this new access system by defining a conceptual model for reviewing access systems. The model studies three access systems: Traditional Access Systems, where most patients are booked into the future; First Generation Open Access Systems, where urgent needs are predicted and responded to daily and routine needs booked into the future; and Second Generation Open Access Systems, where patients are offered an appointment today for any problem and all of today’s work is done today. Note that with the Second Generation system, if the patient cannot attend on the same day, they are booked at some time in the future. Thus, it is rare for any clinic to use a 100% open access system. Murray and Tantau (1999) also defined six dimensions to evaluate these three systems:

- *Capacity. This refers to the amount of space on a schedule that could be used for booking appointments.*
- *Primary sorting and matching criteria. This refers to how clinics match a patient’s request to a service resource.*
- *Holding of appointments. This refers to the practice of holding appointment slots for future demand.*

- *Overflow mechanisms. This refers to the mechanism employed when daily demand exceeds daily capacity.*
- *Accountability. This refers to the provider's responsibility as defined by the clinics. It pertains to the primary obligation for either appointment slots or a panel of patients. For example, in the Second Generation Open Access Systems, providers are accountable for a panel of patients rather than just to fill up the appointment slots, which means providers are more responsible for the health care and patient satisfaction rather than just for the production (filling up the appointment slots) as they are in the traditional and the First Generation Open Access Systems.*
- *Unique issues: These are the specific problems that could happen based on the characteristics of each access system.*

After defining the access model and the six dimensions to evaluate the model, they compared each of these access systems and the results show that the Second Generation Open Access System outperforms the other two access systems in many ways: decreased waits for routine appointments, improved patient satisfaction, as well as reduced cancellations and no-shows.

After open access scheduling was introduced by Murray and Tantau in 1999, many other studies have also been carried to address issues of open access scheduling implementation. These studies will be discussed in detail in this section.

Murray and Tantau (2000) explained how to implement open access in clinics. They first demonstrate:

- The appointment lead-time for open access scheduling is *today*.

- The practices no longer have to hold appointments in anticipation of same-day needs. In other words, they have maximized their capacity (accessibility).
- Since the likelihood that patients will see their regular physicians has increased, service quality and patient satisfaction could also be improved.

After that, they explained how practices can move from a traditional or the First Generation Open Access model to open access scheduling (Second Generation Open Access Model):

- **Commit to how the practice is going to gain capacity.** Under open access scheduling, practices gain capacity by doing most of today's work today, which creates the maximum capacity for tomorrow.
- **Reduce the backlog of appointments.** First of all, practices could use overtime to see as many patients as possible. Secondly, physicians could also reduce backlog by optimizing their time with patients. For example, a doctor could check if the current patient has more appointments on the schedule in the future and ask him/her, "Can I do more with today's visit?"
- **Use fewer appointment types.** Murray and Tantau suggested that in open access scheduling, appointment types should be based on patient-doctor relationship instead of medical issues. This means the number of appointment types can be reduced to three: P (your patients seeing you), T (team: your patients seeing other physicians in your clinical team when you are absent) and U (unestablished: patients are not linked to any particular physician). The P and U appointments are in the same schedule

if the patient's regular physician is working. When the patient's regular physician is absent, the patient will be scheduled with another physician who is in the same clinical team with the patient's regular physician using T type. The appointment lengths are also suggested to be standardized at about 15-20 minutes. These two steps could help practices to simplify their appointment rules, which could lead to error and confusion.

- **Develop contingency plans.** Physicians and clinical teams should plan ahead for how they will handle predictable increases in demand so that the practice can successfully finish today's work today.
- **Reduce demand for unnecessary visits.** Physicians could eliminate unnecessary visits in the future by maximizing today's visits. This tip is similar to what has been suggested in "Reduce the backlog of appointments" earlier.

Also note that in most cases, in order to launch an open access implementation, the clinic will identify a date in the future after which no more appointments are scheduled (generally a few months ahead), and after that date they use open access.

While most other studies have followed what Murray and Tantau (1999) had suggested on how to implement open access (e.g. Carlson 2002, O'Hare and Corlett 2004), Kilo and Endsley (2000) came up with another suggestion to help hospitals implement open access scheduling. They suggest that practices should also enhance their information system, which will result in a better interaction between patients and their physicians as patients can email physicians to ask questions or for follow-

ups. Moreover, patients can make online registration via the clinic's website in order to save the registration time at the clinic.

Murray et al. (2003) described four cases of primary care practices that successfully implemented open access scheduling and three cases of primary care practices that were unable to achieve open access scheduling despite considerable efforts. The lessons of these cases are useful for clinics that want to improve their open access scheduling and to avoid pitfalls that could derail this scheduling system. They found that successful clinics always measured their demand and capacity carefully and they also created team structures to delegate tasks formerly performed by physicians to other practice staff. They also found that open access scheduling was more easily accomplished in smaller private offices. Practices that failed in implementing open access scheduling stumbled for a variety of reasons. The first clinic failed as they never applied the 6 key changes – balancing supply and demand, working down the backlog, reducing appointment types, developing contingency plans, reducing demand, and increasing capacity. The second practice achieved open access scheduling initially, but failed when confronted with abrupt and unexpected changes in supply and demand. The third practice encountered fundamental problems when they were trying to require all their patients to book for same-day appointments over telephone, made it difficult for patients with particular needs for pre-scheduled appointments and the patient satisfaction decreased, resulting in a failure of the implementation.

Murray and Berwick (2003) also explain how to successfully implement an open access system at the end of their article. They point out that the most important

issue for implementing an open access system is to balance supply and demand. They suggest that clinics collect data carefully and accurately by distinguishing first-time visits and follow-ups. They also suggest that clinics should simplify their schedules by only using two types of slots: short and long.

Mehrotra et al. (2008) point out that most studies lack detailed evaluations and relatively few studies had assessed the effect of open access scheduling on outcomes beyond accessibility. They evaluated appointment availability (accessibility), no-show rates, and patient and staff satisfaction in a series of 6 practices. They also examined potential barriers to guide practices that were considering using open access scheduling. In these implementations the clinics gradually attempted to “catch-up” to demand instead of setting a fixed date for launch. They collected data on appointment lead-time, patient and staff satisfaction and no-show rates separately. After analyzing the data, they found that only 5 of the practices reduced their appointment lead-time from 21 days to 8 days for 15-minute visits and from 39 days to 14 days for 30-minute visits within 4 months of implementation; none of them had achieved “same day” access. They didn’t find any consistent change in patient or staff satisfaction or patient no-show rates. After that, they summarized two reasons why these practices ended up failing to implement open access scheduling. These two reasons are also the barriers to implement open access scheduling. One reason is the fluctuations in appointment supply due to unexpected leaves of physicians and the other reason is that it is difficult to assess appointment demand which leads to prolonged planning periods and less enthusiasm and fewer resources devoted to the implementation. Thus, the authors suggest that it is crucial

to accurately measure patient panel size, which is the number of patients under the care of a specific provider. These two barriers are also the reason why the results in this case study are different from the previous ones.

Sections 2.2-2.7 will review what has been studied with respect to factors, performance measures and concepts that are important for this study. Section 2.2 and 2.3 will review the impact of open access scheduling on appointment lead-time and continuity of care. These 2 sections are presented first because the original purpose of implementing open access was to reduce the appointment lead-time and to improve continuity of care. Then, some other issues that have been covered in previous studies such as no-shows and patient visits are presented. Following that, studies focusing on how to balance demand and capacity under open access scheduling, which is a challenging task for both researchers and practitioners due to the nature of this scheduling system, will be reviewed. Finally, articles that have used patient waiting time, doctor idle time and clinic overtime as their performance measures are presented. These measures have been proven to be very important to clinics but have not been studied very often in open access scheduling. The review of these articles will identify gaps and lead to the contribution of this study.

2.2 Appointment Lead-Time

Appointment lead-time is the number of days between the appointment request and the appointment day. It has been reported that a long lead-time can lead to a high no-show rate (e.g. Kopach et al. 2007). Reducing appointment lead-time is one of the two main goals of implementing open access scheduling in practices where

both doctors and patients suffer from long waiting lists and large backlogs. Many studies have been done to show that open access could help clinics and hospitals reduce appointment lead-times. Herriott (1999) suggests in his case study that there is improved patient satisfaction with the length of time between the appointment setting and the actual visit, which reveals a decrease in appointment lead-time after open access scheduling is implemented. Murray and Tantau (2000) claim in their case study that the open access scheduling can help their clinic reduce the appointment lead-time from 55 days to just one day.

Murray and Berwick (2003) explained how the open access scheduling system can help clinics reduce appointment lead-time. They point out that the absolute demand and the absolute supply are usually well matched as long as hospitals and clinics have an appropriate patient panel as no scheduling system can work if physicians have too many patients. They also explained why the traditional access system and the First Generation Open Access System (also referred to as a “carve-out model” in this paper) perform worse in terms of appointment lead-time and the continuity of care. Open access scheduling outperforms the other two systems because clinics create enough capacity for future appointments by “doing today’s work today”. Another reason the open access system is advantageous is that the advanced access model sorts appointment demand by clinician instead of by clinical urgency. This ensures the continuity of care for patients and enables patients to get appointments on the same day when they call.

Pierdon et al. (2004) also demonstrate a reduction in the appointment lead-time in their case study in the Geisinger Health System (GHS), which has a 31-county

service area that spans north-central and eastern Pennsylvania. GHS was facing economic challenges in the 1990's and in many network sites physician schedules were completely booked which resulted in a less-than-desired accessibility. In order to help GHS grow, the authors used open access scheduling to reverse this situation quickly and efficiently. At the completion of implementation, 84% of the primary care sites reduced lead-time to one day or less. These studies only tested the effect of open access on appointment lead-time in primary care practices.

In order to test the effect of open access scheduling on specialty practices, Schall et al. (2004) studied the Veteran Health Administration (VHA), an organization that had implemented open access scheduling in its 1,826 primary care, audiology, cardiology, eye care, orthopedics and urology clinics. Four clinics were highlighted in their case study including 1 primary care clinic, 1 orthopedic clinic and 2 urology clinics. These cases show reductions in appointment lead-time ranging from 20 days to 78 days. This study demonstrates that open access scheduling can reduce appointment lead-time not only in primary care but also in specialty practices.

Knight et al. (2005) also report on a reduction in appointment lead-time in two clinics in Australia and conclude that open access scheduling is feasible in that country.

Although the above case studies have shown a significant reduction in average lead-time for all appointments after implementing open access scheduling, no further statistical tests were made to verify and validate the results. Reductions in appointment lead-time have also been reported by studies using statistical analysis, which makes these results more reliable and robust. For example, Bundy et al. (2005)

used ANOVA to compare the appointment lead-time before and after the clinics implemented open access scheduling. They find that the mean reduction in appointment lead-time is 34 days (from 36 days to 2 days).

Parante et al. (2005) used qualitative analysis first to explain why open access scheduling can help clinics reduce appointment lead-time. They point out that under the traditional scheduling system, patients are unlikely to get an appointment when they call because all the slots on the same day or even for the next few days have already been taken. Instead, they are given an appointment with the next available physician, who may not be the patient's regular physician. However, under open access scheduling, patients are often given an appointment with their regular physicians regardless of their medical issues and thus ideally the appointment lead-time should be one day. Their final statistical test also shows that the reduction in appointment lead-time is significant (from 18.7 days to 11.8 days).

Belardi et al. (2004) also achieved similar results in their study in which they created two teams. One team adopted open access scheduling and the other team used traditional scheduling policy. His final test shows that open access scheduling significantly reduces appointment lead-time from 21 days to between 4 and 7 days. Their use of the control group is a contribution to this field.

O'Connor et al. (2006) demonstrate that open access scheduling can help infant well-child care in reducing appointment lead-time, which can help the practice increase the on-time immunization rate, as infants are more likely to get immunizations on time if the appointment lead-time is short. This result is consistent with the hypothesis of Randolph et al. (2006) that open access should be able to

increase the on-time immunization rate by decreasing the appointment lead-time.

Sperl-Hillen et al. (2008) used logistic regression to test the effect of two aspects, decreased appointment lead-time and improved continuity of care, on the service quality in a diabetes care. Their study shows that after the implementation of open access scheduling, the appointment lead-time does decrease significantly.

Although previous studies have shown, both statistically and qualitatively, that clinics and hospitals can significantly reduce appointment lead-times after implementing open access scheduling, many of them cannot achieve the ideal same-day access as proposed by Murray and Tantau (2000). The papers have explained why practices cannot achieve same-day access. One important reason is that the patient panel size is too large for the practices to handle; another possible reason is the way practices launch open access scheduling. Instead of setting up a fixed date to clean up all the backlogs and to launch open access scheduling, some clinics may have launched open access scheduling while catching up to demand, and thus cannot achieve same-day access.

2.3 Continuity of Care

Continuity of care is the likelihood that a patient can see his/her regular physician. O'Hare and Corlett (2004) report an improved continuity of care in their clinic. After two years of implementing open access scheduling in their clinic, the number of patients who can see their regular physicians increased by 10% (from 65% to 75%). They also report improved quality of care along with the improved continuity of care. However, no statistical analysis was conducted to verify the results.

Belardi et al. (2004) used ANOVA to verify the effect of open access scheduling on continuity of care. Their study focused on a residency family medicine center. They collected data for 15 months and the data were grouped into five 3-month quarters. The implementation of open access scheduling began at the beginning of the second quarter. Their statistical test shows that there is a significant increase in the continuity of care after the implementation of open access scheduling. There is also a significant change between the second and the third quarter. The continuity of care continues to increase at a slower rate for the rest of the quarters, with an over 90% match between patients and their primary care physicians in each quarter. The reason the improvement slows down is that continuity of care had reached a high level, and there was not much potential left for the practices to make any significant improvement. However, the huge improvement between the first and third quarters has demonstrated the great impact of open access scheduling on the continuity of care.

Bundy et al. (2005) report a similar result to that reported in Belardi et al. (2004). They defined successful continuity of care when patients responded, “yes” to the question “Did you see the clinician that you prefer to see today?” They found an increase in continuity of care after the implementation of open access but the increase was not statistically significant, which was due to the short follow-up period after the implementation of open access. The continuity of care in terms of percentage of patients seeing their own physicians in their study was still growing during the last two quarters, which means that the system didn’t reach a steady state when their study ended. It is likely that a significant change will be found if they could extend the length of their study.

Sperl-Hillen et al. (2008) tested the effect of open access scheduling on the quality of diabetes care. They first discovered that after implementation of open access scheduling, the continuity of care was improved. Using logistic regression, they also found that an improved continuity of care is significantly related to the improved quality of care in terms of the percentage of the patients meeting an excellent glucose and lipid control.

Some other studies suggest using primary care groups, in which doctors can take care of each other's patients, to improve the continuity of care. Kennedy and Hsu (2003) did a case study in which they helped the AF Williams Family Medicine Center (AFW) in Denver implement open access system and tracked its performance after the implementation. They redefined the term "continuity of care" as the treatment done by any physician in the same team with the patient's regular physician and encouraged clinics to form physician teams to improve continuity of care.

Delaurentis et al. (2006) found some contradictory results from the ones above. In their simulation results, they first discovered that the percentage of patients using open access scheduling had a significant positive impact on the continuity of care. However, they found that when the percentage of patients requesting open access scheduling increased from 0 to 75%, the probability of the patients seeing regular physicians decreased. Thus, they suggest that clinics can use primary care groups, in which doctors can take care of each other's patients, to help clinics improve the continuity of care when the percentage of patients using open access scheduling is large. This portion is consistent with what Kennedy and Hsu (2003) have found. However, they also found that when the number of patients requesting open access

scheduling increased beyond a certain point, the number of patients served decreased. This finding demonstrates the importance of using a proper percentage of open access slots in practices. However, the lack of the explanation on their simulation model has made it very difficult to interpret the reason behind this issue. One possible reason is that the variable service time causes an excessive waiting time and a long waiting line in the clinic and thus the open access appointment requests made later in the day get rejected.

Kopach et al. (2007) used a simulation technique to analyze the effect of clinical characteristics and open access policies on successful open access implementation. Their simulation results show that if a clinic is too aggressive in implementing open access scheduling (having 75% or more open access slots in a day), the continuity of care would be compromised due to the mismatch between the capacity and demand. Their results also show that provider care groups can help increase the continuity of care. Their finding is consistent with what has been found by Kennedy and Hsu (2003) and DeLaurentis et al. (2006), however, there is no further discussion on the interaction of the percentage of open access slots and the use of provider care groups.

The new definition of continuity of care in the last three studies seems to have helped practices that were suffering from poor continuity of care, but the patients' opinion of this new definition and the use of physician groups has never been taken into account. In other words, the effect of using primary care groups on patient satisfaction and health care quality is unclear.

2.4 No-show Rates

Belardi et al. (2004) used ANOVA to test the effect of open access scheduling on no-show rates. Their results show that open access scheduling can reduce no-show rates, but the reductions are not significant. This is possibly because the no-show rates before and after the implementation of open access scheduling in their study had remained low.

Steinbauer et al. (2006) also report a non-significant reduction of no-show rates. In their study, the no-show rates in the clinics dropped almost to zero after the implementation of open access scheduling. The reason is likely the same as the one above: the no-show rate had been low before the implementation of open access. They didn't find any correlation between no-show rates and the day the appointment is made (same-day vs. previous day), the type of appointments (short vs. long), the status of patients (new vs. return) or the appointment time (morning vs. afternoon).

However, significant reductions in patient no-show rates have been reported. Bundy et al. (2005) and O'Connor et al. (2006) have reported statistically significant reductions in patient no-show rates in their studies, which provides evidence that open access scheduling could reduce no-show rates.

Kopach et al. (2007) carried out a simulation study in which they developed no-show rate function so that the no-show rate can be used as one of the input parameters in simulation modeling. Their function was developed based on the historical data that they had collected and the interviews with the staff working in the clinic, and was found to be an exponential function of appointment lead-time.

Bennett and Baxley (2009) used multivariate regression to test factors that are

related to no-show rates under open access scheduling. They tested a variety of factors that are related to no-show rates and found the factors that are most predictive of no-show rates are appointment lead-time, the number of previous visits, scheduling an appointment with the patient's regular physician, the type of provider (resident vs. faculty), patient race and primary method of payment. Their research found a strong relationship between appointment lead-time and no-show rates and between continuity of care and no-show rates, which added evidence that open access scheduling could reduce no-show rates in healthcare practices.

2.5 Patient Visits

A few studies considered the change in the frequency of visits from the same patient panel after implementing open access scheduling. Kennedy and Hsu (2003) report an increase in the patient visits after the implementation of open access scheduling. Similar results have also been found by Herriott (1999), Pierdon et al. (2004) and Steinbauer et al. (2006). Kennedy and Hsu believe that this is due to fewer no-shows and more consistent scheduling.

In contrast, O'Hare and Corlett (2004) found that the number of patient visits actually dropped. They discovered as patients and doctors developed their relationships, patients became more comfortable asking for more needed services and because physicians were familiar with their own patients, their working efficiencies increased. This to some extent reduced the number of patient visits, but more issues were dealt with per visit.

2.6 Balance Demand and Capacity

A proper patient panel size and an appropriate percentage of open access slots are two crucial elements for practice to match daily demand and capacity. Murray and Tantau (2000) suggest that the appropriate panel size for an individual physician depends on several environmental factors. For example, how many hours the physician is in the office is one of the factors that could influence the panel size. They also suggest that for a full-time family physician in a mature system, the patient panel size could be up to about 2,500.

Green et al. (2007) provided a simple quantitative model to find the optimal patient panel size based on the overflow frequency, which is the probability that the demand will exceed the capacity on a day. It is also suggested that if the overflow frequency in a clinic is low, it is very easy to use overtime occasionally to deal with the excessive demand. The authors suggest that in order to calculate the appropriate panel size, a clinic should identify the current panel size N_{cur} , and calculate the daily visit rate per patient

$$p = \frac{A}{N_{cur} \times T} \quad (1)$$

where A represents the total visits during a certain period of time T. Thus, the overflow frequency is denoted

$$1 - (1 - p)^N - \sum_{k=1}^C \frac{(N-k+1)(N-k+2) \times \dots \times N}{1 \times 2 \times \dots \times k} p^k (1 - p)^{N-k} \quad (2)$$

where C is the number of appointment slots per day; and k is the summation index. It is suggested that clinics could use this method to adjust the patient panel size in order to keep the overflow frequency as low as possible.

Another way to match daily demand and capacity is to set up an appropriate percentage of open access scheduling. Most of the case studies have used a small range of fractions of open slots from 8% to 50%. Kopach et al. (2007) tested two levels, 25% and 75%, separately in their simulation study.

Qu et al. (2007) used an analytical approach to find the optimal percentage of open access appointments to match daily capacity and demand. They used the number of patients consulted as the performance measure, which is denoted

$$Max Q(N_1) = Q_1(N_1) + Q_2(N_1) \quad (3)$$

where $Q(N_1)$ denotes the expected number of patients consulted when at most N_1 appointments could be booked in advance; and $Q_1(N_1)$ and $Q_2(N_1)$ denote the expected number of pre-scheduled and open access appointments separately:

$$Q_1(N_1) = (1 - \gamma_1)E[\min(D_1, N_1)] \quad (4)$$

$$Q_2(N_1) = (1 - \gamma_2)E[\min(D_2, N - \min(D_1, N_1))] \quad (5)$$

where γ_1 and γ_2 represent the no-show rates for pre-scheduled and open access appointments separately, and it is assumed that $\gamma_1 > \gamma_2$; N denotes the number of appointment slots per day; and D_1 and D_2 denote the random demand of pre-scheduled and open access appointments separately; $E[\min(D_1, N_1)]$ represents the actual pre-scheduled demand per day while $E[\min(D_2, N - \min(D_1, N_1))]$ represents the actual open access demand.

They demonstrate that the optimal solution is mainly dependent on the demand for both pre-scheduled and open access appointments and the show rates for both pre-scheduled and open access appointments. This is because the no-show rates increased with the increase in the appointment lead-time, thus, a high

percentage of pre-scheduled appointments will lead to more no-shows; on the other hand, a high percentage of open access appointments will lead to fewer appointments scheduled if there is not enough demand for open access appointments. Both risks will lead to a decrease in the expected number of patients consulted by a provider in a session. By presenting the conditions for the optimal solution and the procedure to find the optimal solution, the authors greatly helped clinical administrators in finding the optimal percentage of open access slots based on their own situation. The limitation of these studies is that they either tried to find the optimal percentage of the open access slots or, in case studies, used a fixed percentage of open access slots. Thus, it is hard to understand how the performance measures change when a clinic moves from a traditional model to an open access model and to provide managerial implications for health care practices with different needs and different proportions of open access slots.

2.7 Patient Waiting Time, Doctor Idle Time and Clinic Overtime

Robinson and Chen (2009) compared the performance of a traditional access policy and an open access policy. They used a weighted sum of physician idle time, patient waiting time and clinic overtime as their performance measurement, and their paper was the first to compare these two systems using analytical methods. Robinson and Chen's (2009) results prove that open access scheduling, in most cases, outperforms traditional appointment scheduling. In particular, open access scheduling will perform better when patients' waiting times matter at least slightly (since if not, the optimal solution for their model would be to just schedule all the

patients at the beginning of the day to eliminate all idle time and to minimize clinic overtime) or when the no-show probability exceeds 5%. The same-day policy is preferable for larger no-show probabilities, for larger workloads, and for surcharges up to 200% on any overtime incurred. Comparing the same-day policy and same-or-next-day policy, they find that the ability to defer patients to the following day can help substantially, especially when the length of the workday is close to the expected workload. This is because a two-day booking window could allow doctors to make more flexible schedules when the demand is high and these flexible schedules could help the clinic to reduce patient waiting time and clinic overtime. One drawback of their model is that the doctor service time is assumed to be deterministic and the open access patient no-show rate is assumed to be zero. These assumptions have resulted in zero waiting time and zero idle time in an open access setting. Another limitation of their study is that the call-in process was not modelled, which has a large impact on whether and when the patient will be scheduled. Despite the above limitation, their contribution is significant not only because of the comparison between the traditional and open access system, but also because of test of the “same-or-next-day” system, which is considered as a way to improve the performance in open access scheduling.

Patrick (2011) built on Robinson and Chen’s study by developing a Markov Decision Model, which allows a clinic to change its booking policy based on the status of the system (the current policy, queue size and demand). They used simulation to compare the Markov Decision Model with open access scheduling (same-day scheduling) in a variety of scenarios that are chosen to compare the system-related

measurements (revenues, overtime and idle time) and the patient-related measurement (lead-time). The results demonstrate that the trade-offs between appointment lead-time and resource utilization need to be considered carefully when selecting different booking policies. It is also demonstrated that open access scheduling outperforms the traditional system, and the same-day-or-next-day system slightly outperforms the same-day access system. This result is consistent with the one in Robinson and Chen's study. The limitation in this study is still the deterministic service time. Patient no-show rate and the call-in process were not taken into account neither. The limitations in both Robinson and Chen's and Patrick's study have shown that analytical methods are limited in their ability to handle uncertainty.

3. Gaps and Contribution

Prior studies primarily focused on how open access could help traditional clinics improve their performance in terms of appointment lead-time, continuity of care, no-shows, patient visits and percentages of open access slots. Robinson and Chen (2009) examined the effect of open access scheduling on patient waiting time, doctor idle time and clinic overtime while Patrick (2011) used a Markov Decision Policy to reduce doctor idle time and clinic overtime. This study adds to the previous literature by investigating different scheduling options to help open access clinics reduce patient waiting time, doctor idle time and clinic overtime.

Herriott (1999) suggests that it is better not to assign early morning slots as open access slots as they might be left open if the call system does not open early or the patients do not call early in the morning. However, due to the different

characteristics of pre-booked and open access patients, placing pre-booked slots at different times in a day may result in different results. This study will investigate the effect of this issue and provide recommendations regarding where to place pre-booked slots.

One of the challenges for open access clinics is how to deal with variable daily demand. In order to help clinics improve their abilities in handling variable demand, a multi-period model will be built in this study. The daily demand will be modeled based on real data collected from an open access clinic. This will add to the previous literature by using a multi-period model to examine the effect of variable demand on clinic performance. Also, different demand levels, which have only been tested in traditional clinics in the previous literature, will be examined in an open access setting in this study, including an overloaded system.

Although prior studies have examined the effect of open access scheduling, some types of data in open access clinics have never been collected before. Data regarding appointment lead-time, continuity of care, patient visits and satisfaction has been collected in some case studies, and empirical data has also been used in analytical studies. However, as far as can be determined, arrival and service time data has not been collected at open access clinics. This study will use data collected from an open access clinic including call arrival times, daily demand and doctor service time. The data collection will help this study create a realistic and accurate model in terms of arrival and service times in an open access setting.

Although prior studies have analyzed some ways that can help open access health care practices to balance demand and capacity, other options have not been

studied. In order to provide more options for clinics to manage the excessive demand, different management options will be tested as the second factor in this study. For example, clinics can also use overtime to deal with excessive daily demand with an open access system. In addition, a third factor, client load, will be used to test the efficiency of the scheduling design in this study. All the above factors will be modeled to add managerial implications to the literature that are suitable for clinics with various needs.

Finally, a simulation technique, which has not been used very often in prior open access studies, will be used in this study to include more uncertainties and more environmental factors.

4. Research Model

4.1 Interview Findings

Before the data collection, an interview was carried out with one of the receptionists in an open access clinic in Hamilton, Ontario. This clinic's phone system is open from 8:30 to 17:00 every day, and they schedule patient appointments from 9:00 to 17:00. There is a one-hour lunch break from 12:00 to 13:00 from Mondays through Thursdays and from 12:00 to 13:30 on Fridays, during which the system does not book appointments. Patients who want to book an open access appointment are encouraged to call between 8:30 and 10:30 since later calls are less likely to be scheduled into the same day. The length of each appointment slot is set to be 15-minutes long, for all patients, resulting in 28 slots on Mondays through Thursdays and 26 slots on Fridays.

The clinic has three health care teams, which include doctors, residents, receptionists and nurses. The interview was based on one of the teams formed by 5 doctors and 11 residents. Doctors and residents in this team use 30% percent of their daily slots as pre-booked slots and 70% of their daily slots as open access slots. The pre-booked slots are placed at the beginning of each day. Although the clinic does not use a fixed or maximum time horizon to book routine patients, the appointment lead-time for pre-booked appointments is always approximately one week, which reveals a constant demand for pre-booked appointments.

The clinic receives the most calls on Mondays and fewer calls on the other days of the week. When the demand exceeds their daily capacity, the receptionists would ask the patients if they want to be booked with another physician or if they want to be pre-booked into the future; sometimes the receptionists would also ask patients to call back on the next day when their regular physicians are working.

The information above was then found to be reliable through the later data collection process, and how the interview information is used will be explained in later sections.

4.2 Simulation Model

Call arrival data and service time data were collected in the clinic. Call arrival data was collected by the receptionists in the clinic for a Monday and a Thursday. The receptionists recorded the arrival time of each call for each doctor in the team and the arrival time was rounded up to the nearest minute. One doctor was observed; this doctor worked Mondays, Wednesdays and Thursdays. Service time data was

collected by observing the time when doctor walked into the service room and the time that the service ended, for 6 business days. The difference between these two time points was used to represent doctor service time. The final type of data collected was the patient no-show rate for both pre-booked patients and open access patients. According to a study carried out by the clinic, in 2009 the no-show rate was 4.22% for pre-booked patient and 2.05% for open access patients.

A simulation model was built based on the interview information and the data collected from the clinic. Each appointment is 15-minutes long for all patients. The phone system works from 8:30 to 17:00 and the clinic starts to serve patients at 9:00 every day. There is a one-hour lunch break on Mondays through Thursdays. This approach results in 28 slots on each day, with the first 8 slots being pre-booked slots and the rest of the 20 slots being open access slots. Calls arrive randomly throughout the regular working hours. In order to input the call arrival data into the model, the inter-arrival time between calls was then calculated. Forty-six observations were analyzed with the Input Analyzer module in Arena 10 after deleting outliers. The result of the analysis suggests that the data follow an exponential distribution with a mean of 13.8 minutes. This distribution has been widely used in previous studies due to its ability to represent the independent manner for call arrivals (Klassen and Rohleder, 2002). After that, a non-stationary Poisson arrival process was constructed based on the distribution since the call arrival rates varied across the working hours. In this case, a 30-minute time interval was used within which the call arrival rates appeared to be fairly flat. The arrival rate for each half hour was then determined using a piecewise-constant rate function. There were 22 open access calls on Monday

and 16 open access calls on Thursday. This is in line with the interview findings. Since the interview suggested that the demand on Wednesdays and Thursdays were quite similar, the Thursday data were used to represent Wednesday's open access demand. The call arrival rate for each 30-minute period is presented in Table 1 and Table 2.

Table 1
Monday's Demand

Time	Rate	Time	Rate	Time	Rate
8:30-9:00	2	11:00-11:30	2	14:30-15:00	1
9:00-9:30	4	11:30-12:00	1	15:00-15:30	1
9:30-10:00	2	13:00-13:30	2	15:30-16:00	0
10:00-10:30	3	13:30-14:00	1	16:00-16:30	0
10:30-11:00	2	14:00-14:30	1	16:30-17:00	0

Table 2
Wednesday and Thursday's Demand

Time	Rate	Time	Rate	Time	Rate
8:30-9:00	2	11:00-11:30	1	14:30-15:00	0
9:00-9:30	3	11:30-12:00	2	15:00-15:30	3
9:30-10:00	2	13:00-13:30	1	15:30-16:00	0
10:00-10:30	1	13:30-14:00	0	16:00-16:30	0
10:30-11:00	1	14:00-14:30	1	16:30-17:00	0

Following that, the service time data and the no-show data were also integrated into the model using the same approach. The Input Analysis showed that

service times followed a Weibull distribution (mean=16.14, standard deviation=7.35) with $\beta = 11.1$ and $\alpha = 2.1$. The Weibull distribution has been widely used in previous studies to represent doctor service times and other non-negative task times (Liu and Liu, 1998; Denton and Gupta, 2003).

There are several assumptions to support the simulation model:

- *This is a single-server model and the doctor only works three days in a week (Monday, Wednesday and Thursday);*
- *Based on the interview information, it is assumed that Wednesday's demand and Thursday's demand are the same. Thus, Thursday's call arrival data was used to represent Wednesday's demand as well;*
- *In order to allow clients time to travel to the clinic, it is assumed that the soonest a client could be scheduled in the model is 30 minutes after their call;*
- *Patients arrive at the clinic punctually;*
- *Doctors do not leave the clinic until 17:00, which is the same as in the real clinic;*
- *The interview revealed a constant demand for pre-booked appointments in the clinic. The lead-time for pre-booked appointments is always one week. Thus, it is assumed that all the pre-booked slots are full in the model.*

A detailed flowchart demonstration of the simulation model and the motivation for the research methodology are presented in Section 5.

4.3 Factors Tested

Three factors will be tested this in study: Client Load (CL), Management Options for Excessive Demand (MO) and Pre-booked Slots Placement (PSP). These

factors are believed to have an impact on the performance of open access clinics since all three can affect the balance between the demand and capacity in open access clinics. The results are expected to provide practical and useful information for open access clinics to improve their performance.

4.3.1 Client Load

Client load (CL) is expected to have an impact on the clinic performance since an over loaded system could present challenges (Klassen and Rohleder 2004). Under the factor “CL”, three different loads for open access demand are tested. A 100% loaded system will be modeled as a base-case. Two other loads, 80% and 120% are also examined to test the clinic’s performance when dealing with underloaded and overloaded scenarios. The 80% loaded system is expected to have more idle time while the 120% loaded system is expected to have more waiting time and overtime. The results of the test on this factor are expected to show the importance of the balance between the demand and capacity for open access clinics and to provide guidance for open access clinics to deal with seasonal demand variation.

4.3.2 Management Options

Four different management options will be tested under this factor. When facing higher than usual demand, two approaches are often used in clinics: 1) double-booking patients by putting two patients into the same appointment slot, and 2) overtime (Klassen and Rohleder, 2002). These two approaches are the first two levels under this factor. In the clinic where the data was collected, receptionists would

sometimes ask the patients to call back if the same day's schedule is full; they would also schedule patients into the next day where an open access slot is available with their regular physicians. These two approaches are the other two levels under this factor. In fact, the clinic has even more options to deal with excessive daily demand. For example, sometimes the receptionists would schedule patients with other physicians on the same team when their regular physicians are not available. However, this situation cannot be modeled in this study since only one server is modeled. The effect of these options is highly unpredictable since clinics may perform better in one aspect, but may perform worse in other aspects by using the same option. A description of the levels under this factor is presented in Table 3 below.

Table 3
Management Options for Excessive Demand

Levels	Abbreviation	Description
Call Back	CB	Patient will be asked to call back on the next day that their regular physician is working
Double Booking	DB	Double book patient
Overtime	Overtime	Schedule patient into overtime
Schedule into Next Day	SND	Schedule patient into the next day's open access slots that their regular physicians are working

Note that when double booking is used, if patients call in later in the day and all the remaining slots are double booked, overtime will be used to ensure same day access.

4.3.3 Pre-booked Slots Placement

Herriott (1999) has suggested that open access clinics should put their pre-booked slots at the beginning of the day. This seems reasonable since if clinics designate early morning slots as open access slots and the phone lines in those clinics don't open very early in the morning, it is very likely that those early morning open access slots would go unfilled. However, since open access patients and pre-booked patients have different no-show rates, putting pre-booked slots at different times of day may have different impacts on clinic performance.

The first level under this factor, "Beginning", is the same as Herriott's (1999) suggestion - placing pre-booked slots at the beginning of the day. In this scenario, 8 pre-booked slots are created from 9:00 to 11:00. The second level is "Middle" with 4 pre-booked slots at the end of the morning clinic session - from 11:00 to 12:00 and 4 pre-booked slots at the beginning of the afternoon clinic session - from 13:00 to 14:00. The third level is "End", with 8 pre-booked slots at the end of each clinic day, from 15:00 to 17:00.

Note that since the real clinic has a constant appointment lead-time for pre-booked patients - approximately one week, it is assumed that all the pre-booked slots are always booked in the simulation model.

A summary of all the factors and levels is presented in Table 4.

Table 4
Factors Tested

Factors	Abbreviation	Levels
Client Load	CL	80% 100% 120%
Management Options	MO	Call Back (CB) Overtime (Overtime) Double Booking (DB) Schedule into Next Day (SND)
Pre-booked Slots Placement	PSP	Beginning of the day (Beginning) Middle of the day (Middle) End of the day (End)

4.4 Performance Measurement

To describe the model mathematically, define:

N = total number of patients seen during the day;

ST_i = service time for patient i , $i = 1, 2, 3, \dots, N$;

AT_i = appointment start time for patient i ;

WT_i = waiting time for patient i ;

IT_i = doctor idle between patient i and $i - 1$;

D = scheduled day end time (17:00 in this study);

OT = clinic overtime.

The goal of this study is to minimize the patient waiting time, doctor idle time and clinic overtime. Patient i 's waiting time can be described as:

$$\begin{cases} WT_1 = 0 \\ WT_i = \max\{AT_{i-1} + WT_{i-1} + ST_{i-1} - AT_i, 0\}, \text{ for } i = 2, 3, 4, \dots, N \end{cases} \quad (6)$$

Similarly, doctor idle time for patient i can be calculated as follows:

$$\begin{cases} IT_1 = 0 \\ IT_i = \max\{AT_i - (AT_{i-1} + WT_{i-1} + ST_i), 0\}, \text{ for } i = 2, 3, 4, \dots, N \end{cases} \quad (7)$$

The above formula applies for all situations (including overtime), except for after the last patient when there are no overtime patients (doctors always stay until 17:00). The last patient scheduled during normal working hours will be denoted by “ l ”. Therefore, when there are no patients scheduled in overtime, doctor idle time between when the last patient scheduled before 17:00 is finished being served and the scheduled day end time can be defined as:

$$IT_l = \max\{0, D - (AT_l + WT_l + ST_l)\} \quad (8)$$

Finally, clinic overtime can be demonstrated as:

$$OT = \max\{0, AT_N + WT_N + ST_N - D\} \quad (9)$$

The primary performance measurement is denoted as:

$$\min C = E\{\sum_{i=2}^N WT_i\} + E\{(\sum_{i=2}^N IT_i) + IT_l\} + E\{OT\} \quad (10)$$

$$\text{s.t. } \begin{cases} AT_1 = 0 \\ AT_i = AT_{i-1} + 15, \text{ for } i = 2, 3, 4, \dots, N \end{cases} \quad (11)$$

$$AT_1 \leq AT_2 \leq AT_3, \dots, AT_N \quad (12)$$

$$AT_i \text{ integer.} \quad (13)$$

Note that appointments are booked into overtime at the regular 15 minute intervals.

Many prior studies have weighted doctor idle time more than patient waiting time in an effort to more accurately mimic reality and to generate more reasonable schedules (e.g., Klassen & Rohleder, 1996; Klassen & Yoogalingam, 2009). In this study, doctor idle time is weighted at two levels; equally and at 10 times more than waiting time. Pretesting shows some of the results changed slightly by weighting the

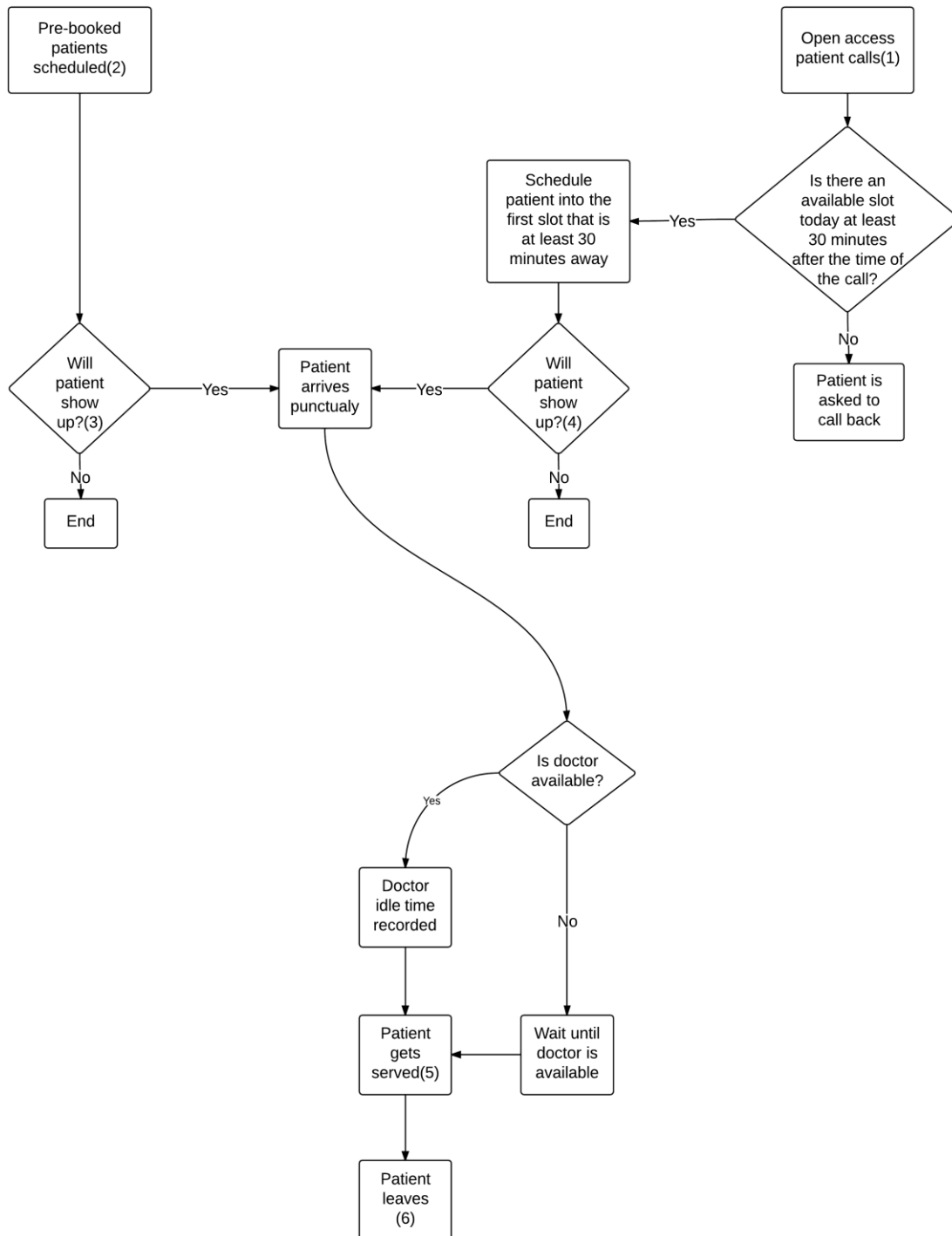
cost of doctor idle time and these changes will be presented and discussed in later sections.

Also, in order to make the model more generalizable, higher no-show rates are tested. A no-show rate of 35% for pre-booked patients and a no-show rate of 17.5% for open access patients are tested for all scenarios and the changes in the results will be demonstrated in later sections.

5. Research Methodology

This study uses simulation modeling, including subsequent statistical tests. Many researchers have suggested that simulation modeling is a useful tool to examine systems that involve a high level of complexity and uncertainty. Due to the complex nature of the health care industry, a large number of prior studies have used it as a research method. Open access scheduling is a more complex system than the traditional scheduling system since it involves more uncertainties such as variable daily demand, a more complex scheduling process and different characteristics of pre-booked patients and open access patients. Simulation also has the ability to test multiple scenarios. Thus, simulation modeling is the best method to be used in this study. The use of the data and the retrieval of the data from the simulation model is presented in a flowchart in Figure 1:

Figure 1
General model flowchart



(See next page for notes)

Notes for Figure 1:

- (1) *As mentioned earlier, open access call arrivals follow a non-stationary Poisson arrival process. The arrival rate for each 30-minute period is shown in Table 1 and Table 2. Once these rates are input into the simulation model, Arena 10 will generate open access calls base on this arrival pattern.*
- (2) *Eight pre-booked patients are generated one at a time from 9:00 to 10:45 every day by the simulation model. The inter-arrival time of pre-booked patients is 15 minutes.*
- (3) *According to the collected data, the no-show rate for pre-booked patients is 4.22%, which could help the model decide what percentage of pre-booked patients will actually arrive at the clinic. The model will dispose the patients who fail to show up.*
- (4) *Similarly, the collected data will also help the model decide what percentage (2.05%) of open access patients will show up for their appointments. Patients who fail to show up will also be disposed.*
- (5) *Patients will be served by the doctor during this process. The service time for each time follows a Weibull distribution ($\beta=11.1$ and $\alpha=2.1$). The variable service time could generate patient waiting and doctor idleness. The doctor can start serving the next patient as soon as he or she finishes serving the current one if there is a patient waiting.*
- (6) *Day end time will be recorded after the last patient is served on each day in order to calculate clinic overtime.*

After simulation is used, results will be analyzed using ANOVA and follow-up testing, using SPSS. The factors tested in this study result in 36 scenarios ($3 \times 3 \times 4$). Each run was one-month (12 working days), and was replicated 1000 times. The 1000 values were then grouped by 10 and averaged, creating 100 observations for each scenario. Pre-testing showed that this approach ensured normally distributed outputs for the performance measurement in most of the scenarios.

6. Results and Discussion

Table 5 provides the final results for the primary performance measure (equation 10) for all 36 scenarios with 95% confidence intervals in the brackets. A 3-way ANOVA test was conducted using the GLM module in SPSS to examine the effect of CL, MO and PSP. The results of the 3-way ANOVA are presented in Table 6.

Table 5

Performance Measure: Mean (95% confidence interval)									
PSP	Beginning	80%		Beginning	100%		Beginning	120%	
		Middle	End		Middle	End		Middle	End
CB	184.4 (+/-0.9)	191.8 (+/-0.8)	273.0 (+/-0.6)	156.5 (+/-0.9)	173.8 (+/-0.8)	258.7 (+/-0.6)	142.9 (+/-0.8)	163.8 (+/-0.8)	249.6 (+/-0.5)
DB	189.4 (+/-0.9)	203.2 (+/-1.0)	272.2 (+/-1.1)	180.7 (+/-1.2)	212.2 (+/-1.3)	276.5 (+/-1.2)	204.5 (+/-1.6)	245.7 (+/-1.4)	295.3 (+/-1.3)
Over-time	189.2 (+/-0.9)	202.6 (+/-0.9)	390.9 (+/-1.3)	178.4 (+/-1.0)	209.2 (+/-1.1)	422.5 (+/-1.3)	197.6 (+/-1.1)	238.7 (+/-1.4)	464.1 (+/-1.4)
SND	180.4 (+/-0.9)	184.8 (+/-0.9)	219.8 (+/-0.5)	147.1 (+/-0.7)	153.7 (+/-1.1)	217.8 (+/-0.5)	135.4 (+/-0.7)	137.4 (+/-0.6)	218.1 (+/-0.7)

Table 6 shows that all the main effects and interactions are significant at the 0.05 significance level. The R Squared (.995) value shows that the model explains 99.5% of the total variance. The main effects account for 78.4% of the total variance. Post hoc tests (Tukey HSD) were also conducted to test which means differ. All the post hoc tests show a significant difference; therefore these are not discussed directly, but they show that we can be sure that the results discussed in this section are statistically different. The post hoc tests are provided in the Appendix.

Table 6

3-way Factorial ANOVA						
Dependent Variable: Performance Measurement						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	19725831.830 ^a	35	563595.195	22076.481	.000	.995
Intercept	176091894.389	1	176091894.389	6897662.397	.000	.999
CL	56462.681	2	28231.341	1105.845	.000	.383
MO	5027121.882	3	1675707.294	65638.814	.000	.982
PSP	10458075.532	2	5229037.766	204825.653	.000	.991
CL * MO	629719.863	6	104953.311	4111.106	.000	.874
CL * PSP	119495.742	4	29873.935	1170.186	.000	.568
MO * PSP	3348210.688	6	558035.115	21858.688	.000	.974
CL * MO * PSP	86745.442	12	7228.787	283.157	.000	.488
Error	90986.116	3564	25.529			
Total	195908712.334	3600				
Corrected Total	19816817.946	3599				

a. R Squared = .995 (Adjusted R Squared = .995)

6.1 Client Load

All results are initially discussed for the case where idle time is weighted equally with waiting time. Changes in results when idle time is weighted more than waiting time and when no-shows are higher are then discussed at the end of each section.

One objective of this study was to explore the effect of CL. The effect of this factor is presented in Figure 2

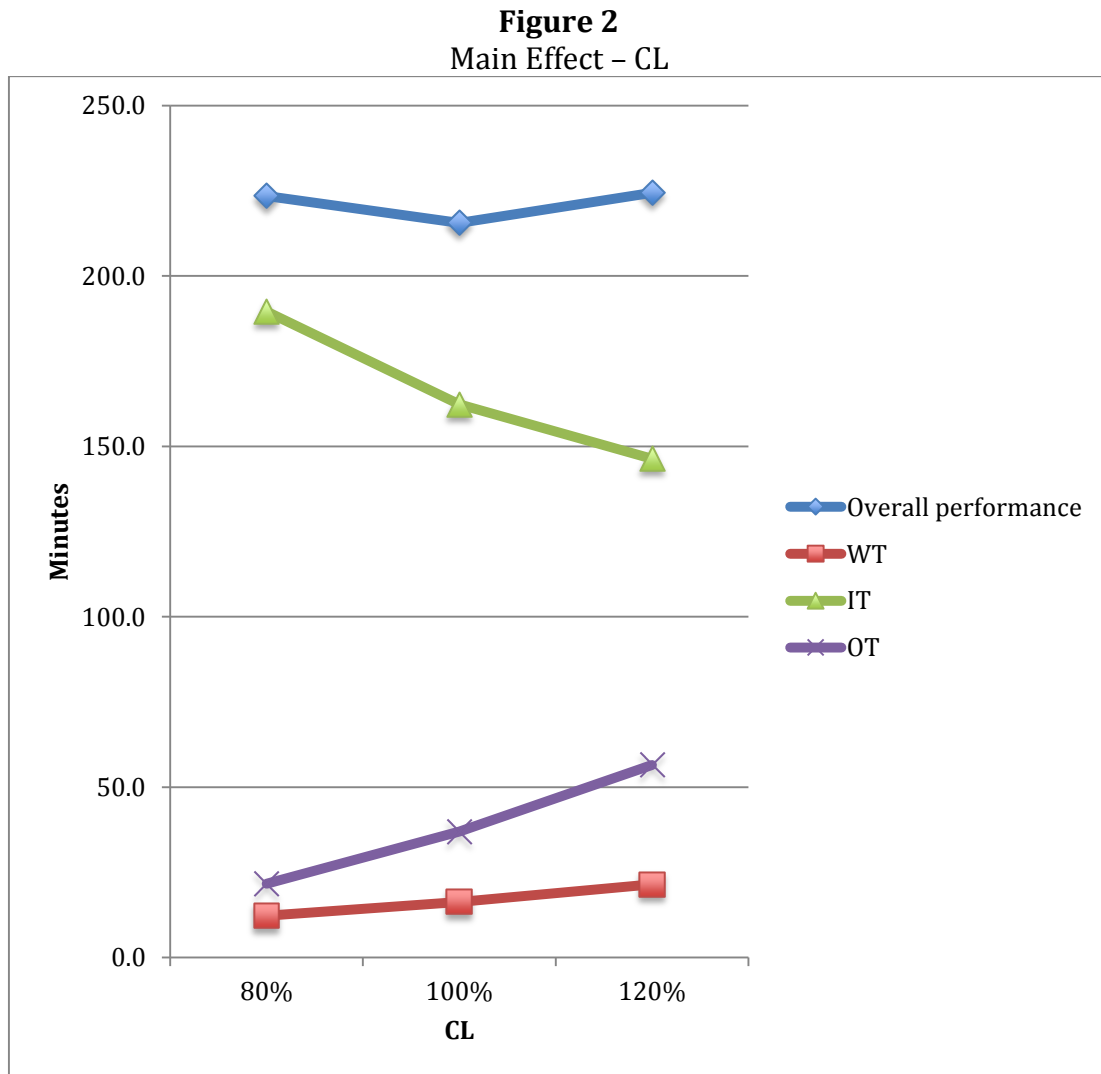


Figure 2 shows that with 100% load, the clinic has the best overall performance. Performance becomes worse when the clinics is either underloaded (with 80% load) or overloaded (with 120% load). However, the WT, IT and OT lines have revealed that the 80% loaded system and the 120% loaded system performed worse than the fully loaded system for different reasons. Although the 80% loaded system generates less WT and OT than the fully loaded system, its' extremely high IT has resulted in a worse overall performance than the 100% load case. In contrast, although the 120% loaded system has the least IT, its' worse performance in both WT and OT has resulted in its overall performance being the worst.

This result has shown the importance of balancing the demand and capacity for open access clinics. With the 80% load, the system will of course create the least WT and OT, but the extremely high IT has revealed a waste of resources. However, in practice, the system is unlikely to be underloaded. On the other hand, if open access clinics are facing a higher than usual demand for a long period of time, the long WT and OT would become a very serious problems. Patient and staff satisfaction could not be guaranteed. In fact, as mentioned by Murray and Berwick in 2003, clinics could not ensure open access scheduling if the demand is always higher than capacity since constant excessive daily demand could lead to enormous backlogs. Thus, a proper panel size is critical for open access clinics.

When the cost of doctor idle time is weighted more, the overloaded system significantly outperforms the other two levels due to its low idle time. When no-show rates are high, the overloaded system still outperforms the other two levels, however, it is only slightly better than the fully loaded system.

6.2 Management Options

Another objective of this study was to test the effect of MO and it turned out that this factor had a relatively large impact on the clinical performance since it accounted for 25.4% of the overall variance. Figure 3 shows that clinics with different MOs performed quite differently. It has been found that SND is the best rule. Since no patients are double booked or scheduled into overtime, SND creates relatively low WT and OT. The reason why it also performed very well in IT is that it has the ability to smooth out excessive demand. In this model, the demand is higher than the capacity on Mondays and some of the Monday's patients are scheduled into Wednesday using SND. Similarly, excessive Wednesdays' demand could also be scheduled into Thursdays where demand is also lower than the capacity. The buffering role that Wednesdays and Thursdays play helps the system schedule excessive demand on Mondays into the next two days without creating OT. This also shows that a two-day booking window performs better than the same-day policy, which is in line what has been found by Robinson and Chen (2009). However, a drawback of SND is that it will result in some patients not being scheduled after a one-month period, especially when the system is overloaded. This, to an extent, biased the result. The average number of patients who are not seen and the average appointment lead-time in each scenario with SND are presented in Table 7 and Table 8.

Table 7

Average number of patients not scheduled for SND			
	80%	100%	120%
Beginning	3.6	6.0	26.6
Middle	3.8	6.8	27.8
End	25.4	61.5	100.7

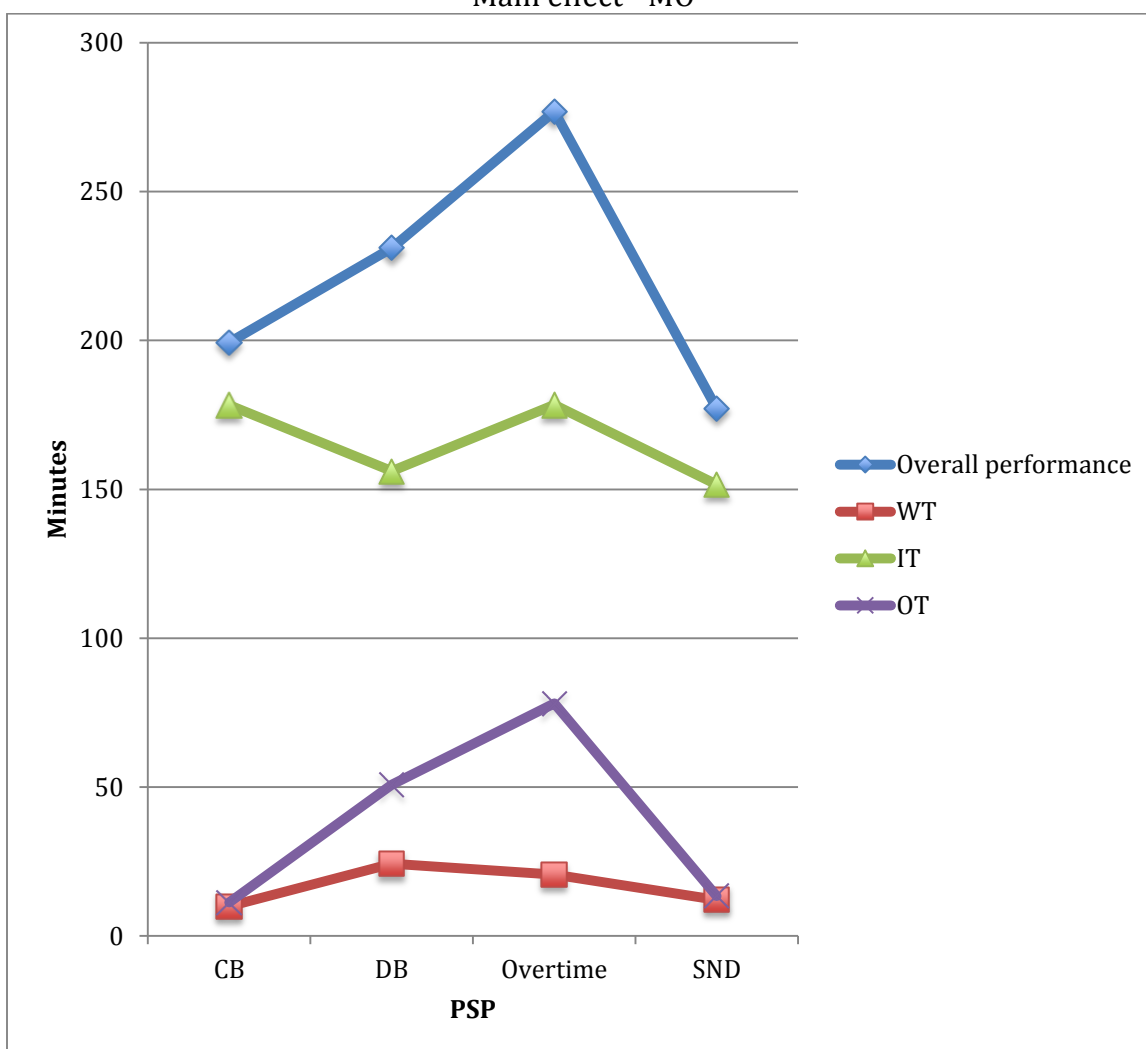
Figure 3
Main effect - MO

Table 8

Average lead-time for open access patients(in days)			
	80%	100%	120%
Beginning	0.03	0.14	0.61
Middle	0.05	0.20	0.67
End	0.89	1.28	1.40

Figure 3 also shows that CB is the second best rule. However, the corresponding result is also biased since the callbacks are not modeled in this study. Although CB is one method the clinic studied uses, they had no data at all in regard to how many patients actually call back. They are reflected in the data collected, but the number is unknown. As a result of the lack of information, some patients may not ever be served in the model. It is impossible to know how many actually call back, but the average number of patients who are asked to call back in each scenario is presented in Table 9.

Table 9

Average number of patients who are asked to call back			
	80%	100%	120%
Beginning	4.013	15.531	38.331
Middle	7.713	24.82	51.786
End	78.935	107.094	138.79

It can be identified from Table 9 that as the CL increases, the number of patients who have been asked to call back increases too. The situation becomes highly unacceptable when clinics place the pre-booked slots at the end of each day.

Unsurprisingly, DB and Overtime are the two worst rules due to their long waiting time and overtime. With DB, patients are double booked when the current schedule is full, which effectively mitigates the effect of no shows, with IT being reduced significantly. However, this effect is not significant enough to offset its effect on WT and OT. By putting two patients into the same slot, this rule creates much more WT and OT than CB and SND, causing its overall performance to be worse.

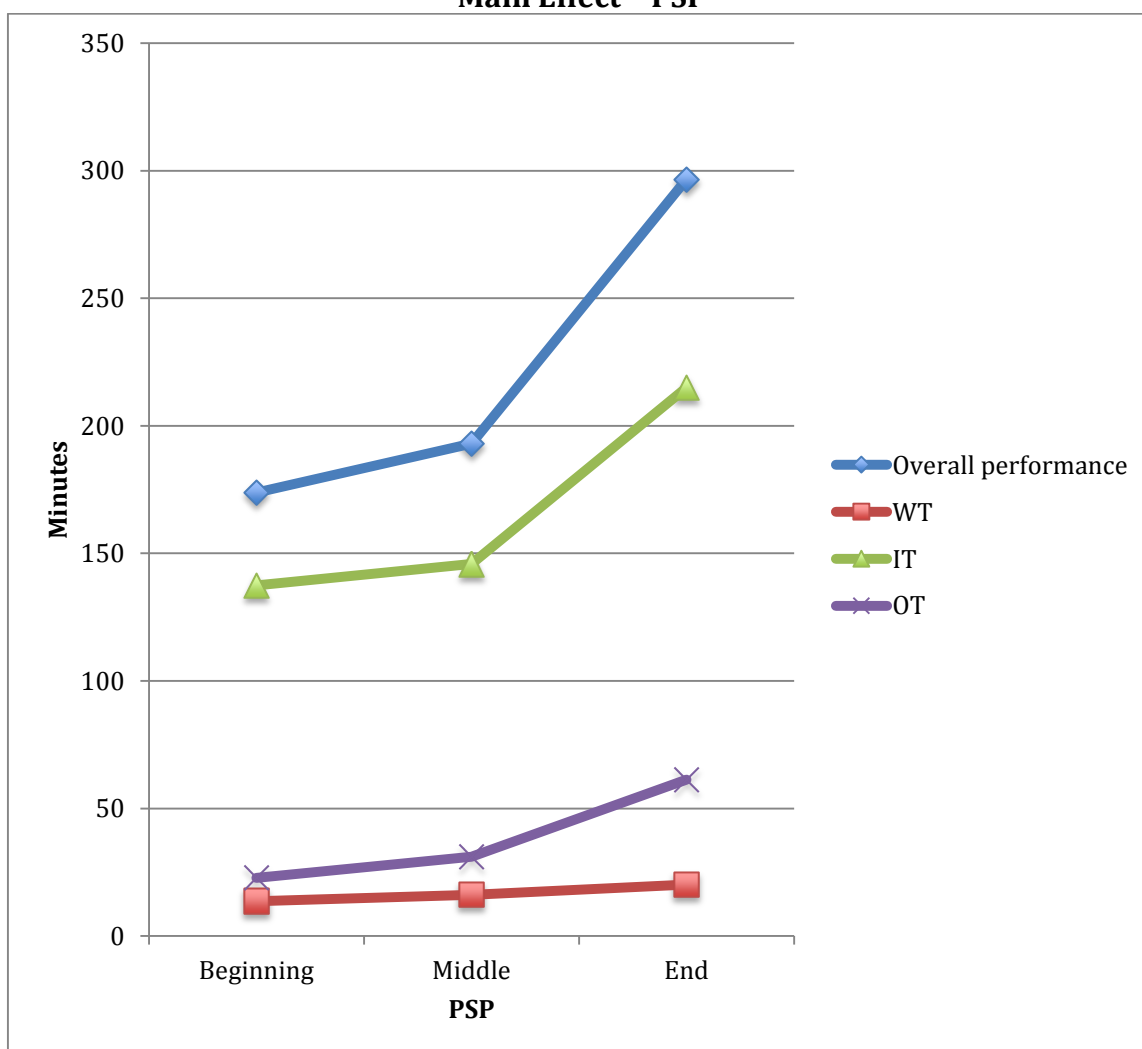
Overtime is worse than DB for a couple of reasons. First of all, it directly generated a large amount of OT, which is part of the overall performance measure. Secondly, this rule generates more IT than DB during the regular working hours and more WT than SND and CB during the overtime. All these factors have led to it having the worst performance among all the 4 options.

Results change when the cost of doctor idle time is weighted more. Unsurprisingly, the rules that generate the least idle time, DB and SND, outperform the other two significantly. However, SND is still the best rule due to its lower waiting time and overtime. The results remain almost the same with high no-show rates, with DB only slightly outperforming CB.

6.3 Pre-booked Slots Placement

The final factor tested in this study is PSP and, according to the ANOVA table, it had the most significant impact on the overall clinical performance with 52.8% of the total performance explained. The effect of PSP is presented in Figure 4. It has been shown that Beginning performed better than Middle and End in all cases, which leads to it having the best overall performance. This is in line with what has been suggested by Herriott (1999).

Figure 4
Main Effect - PSP



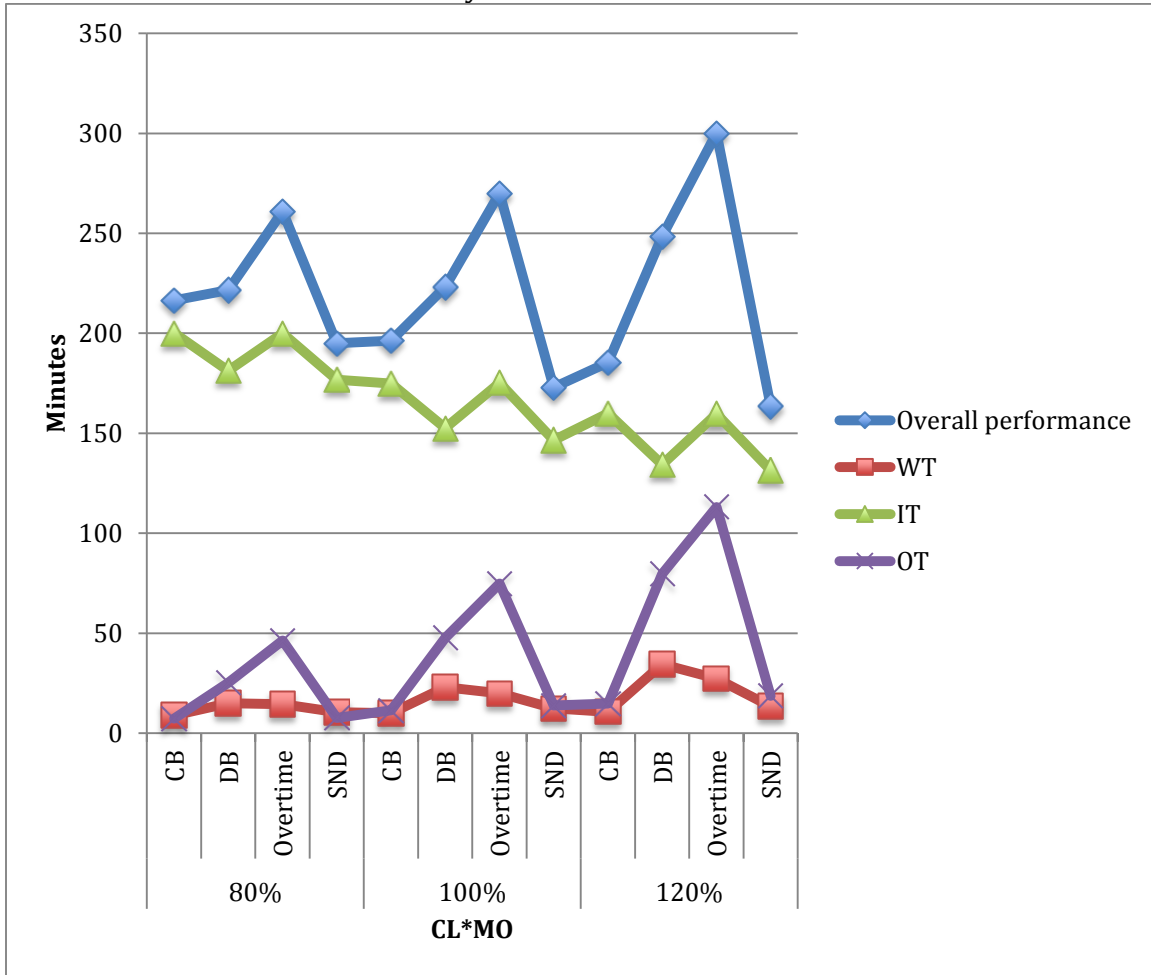
Middle and End performed worse than Beginning for similar reasons. Placing pre-booked slots at either the middle or end of the day may result in some of the early morning open access slots being unfilled. This not only increases the IT but also increases WT and OT since the schedules are more intensive than Beginning after the first few calls are scheduled in the morning.

Since the effect of PSP is so significant, it reminds the open access clinics that placing pre-booked slots at the beginning of each day should be the only option to consider at all times. Either Middle or End will significantly reduce overall clinical performance. The results didn't change when the doctor's idle time is weighted more or when higher no-show rates are used.

6.4 CL*MO

Figure 5 illustrates a 2-way interaction analysis between CL and MO. There are two different trends of MO across CL. SND and CB are the two best rules and they have the same patterns over the levels of CL – the performances of SND and CB become better as the load increases. Although the load increases from 80% to 120%, the WT and OT for SND and CB still remain much lower than the other two levels since patients are neither double booked nor scheduled into the future. This is the main reason why SND and CB are always better than the other two levels. SND outperforms CB due to its lower IT. Clinics using SND schedule excessive daily demand into the next day and could see more patients than those that are using CB, which is the reason why SND's idle time is lower.

Figure 5
2-way Interaction – CL*MO



On the other hand, DB and Overtime are the two worst rules and they have the same patterns over the levels of CL as well – overall performance becomes worse when the load increases. As mentioned earlier, the WT and OT for DB and Overtime become extremely high when the load increases, which is the reason why their performances are worse than SND and CB. Overtime's performance is worse than DB since it has more IT. With Overtime, any excessive demand is scheduled into overtime

while the IT in the regular hours is not improved, which is why Overtime's IT is higher than DB's.

Recall that with 120% load, CB and SND could both result in some patients not being served, and therefore the results here should be treated with caution. Thus, DB and Overtime are the only two options to deal with excessive demand. This analysis demonstrates that a 100% load is ideal for open access clinics. Similar to Section 6.2, CB becomes worse when weighting the cost of doctor idle time more.

The results changed slightly with higher no-show rates as DB effectively reduces doctor idle time and outperforms CB and Overtime in an underloaded and a fully loaded system. However, for the 120% load, DB is still the second worst rule due to the high WT and OT.

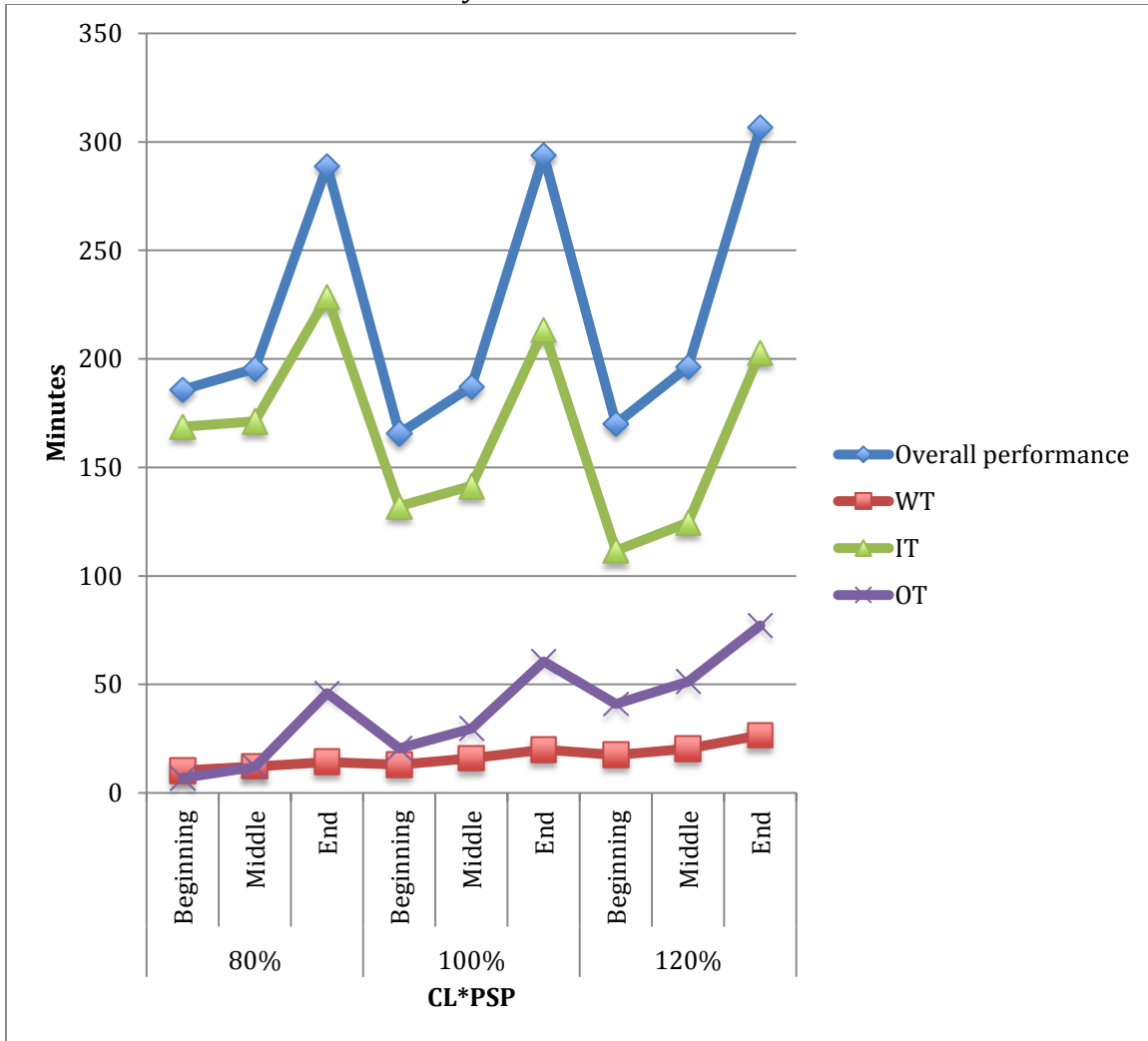
6.5 CL*PSP

A 2-way interaction between CL and PSP is shown in Figure 6. The PSP levels reveal two different trends across CL. While the performance of End becomes worse when the load increases, Beginning and Middle perform better with 100% load than any other load. As in the main effect analysis, Beginning is still the best option for open access clinics to place their pre-booked slots regardless of the levels of CL.

Table 1 and Table 2 showed that approximately half of the calls arrive between 8:30 and 10:30 every day, and only a few calls arrive in the afternoon. With a first call first schedule basis, End creates the most intensive schedule after the first few patients are scheduled with the last two hours filled up already. This is why End has more OT and WT than the other options. Unfortunately, IT is not improved by this

intensive schedule because early morning open access slots are not filled and pre-booked patients have higher no show rates at the end of each day. Therefore, the overall performance of End becomes worse when the load increases.

Figure 6
2-way Interaction – CL*PSP



Both Beginning and Middle are significantly better than End. Similar to End, Middle creates more WT, OT and IT than Beginning, causing its overall performance being worse than Beginning. It could also be identified that the performances of

Beginning and Middle with 80% load are worse than the 100% load. This may be initially surprising, but it is reasonable because the IT is extremely high if the demand is lower than the capacity.

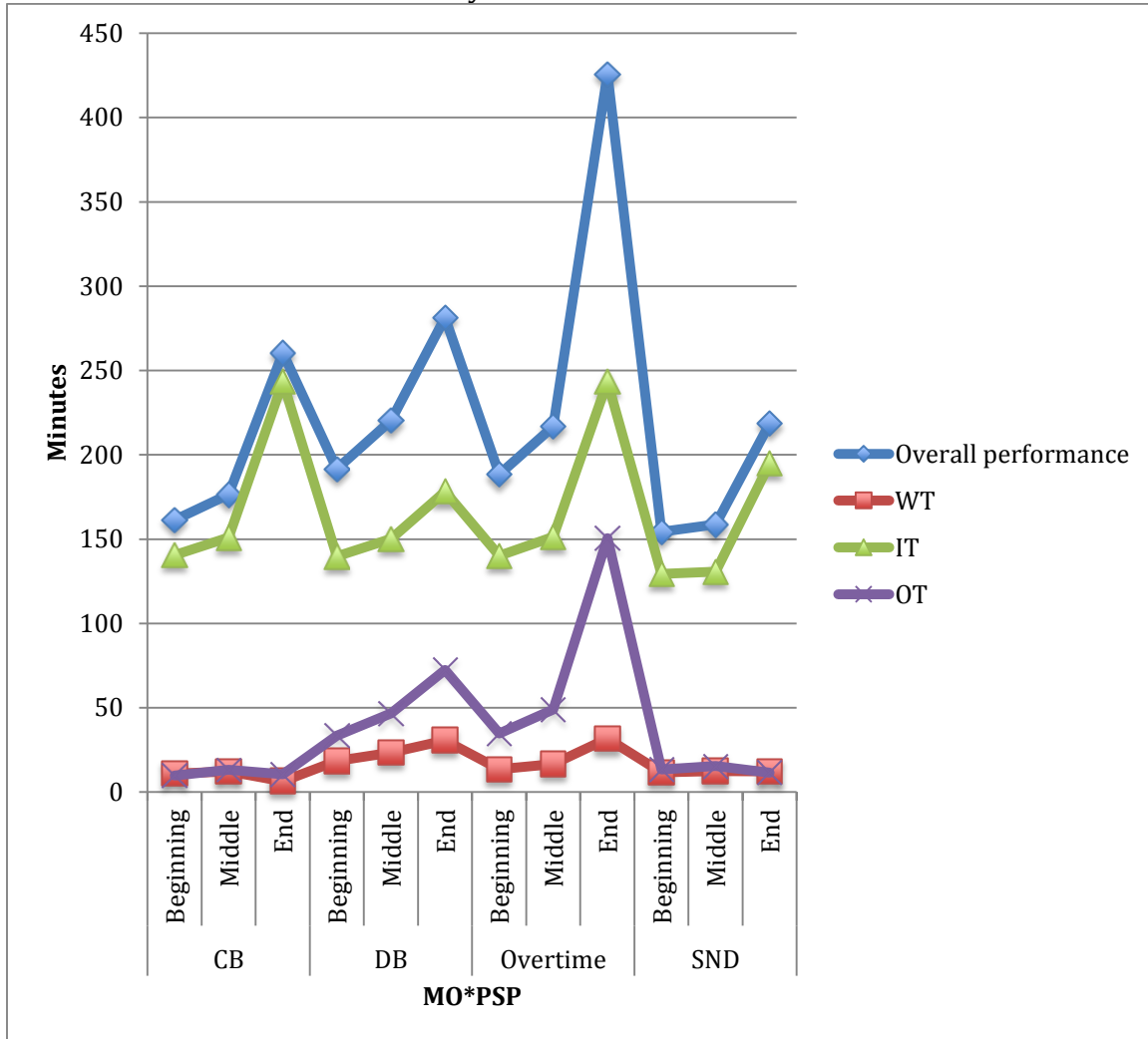
Again, since PSP has accounted for such a large amount of variance, it is recommended that Beginning should be the only way for open access clinics to place their pre-booked slots. And with this setting, a 100% load is again shown to be ideal for open access clinics. However, when the cost of doctor idle time is weighted more, 120% turns out to be ideal since it generates the least idle time.

6.6 MO*PSP

Figure 7 demonstrates the result of the 2-way interaction analysis between MO*PSP. Unsurprisingly, all the MO levels have the best performances if the pre-booked slots are placed at the beginning of each day.

With Beginning, the ranking of the performances of the levels under MO is slightly different from the earlier analysis. Overtime, in this case, outperforms DB and becomes the third best rule. Recall that the rules under MO are only executed when the daily schedule is full. Thus, the OT and IT for DB and Overtime are approximately the same. What really differentiates these two rules is the WT. By putting two patients into the same slot when the daily schedule is full, more patients wait, and this creates more WT than Overtime does.

Figure 7
2-way Interaction MO*PSP

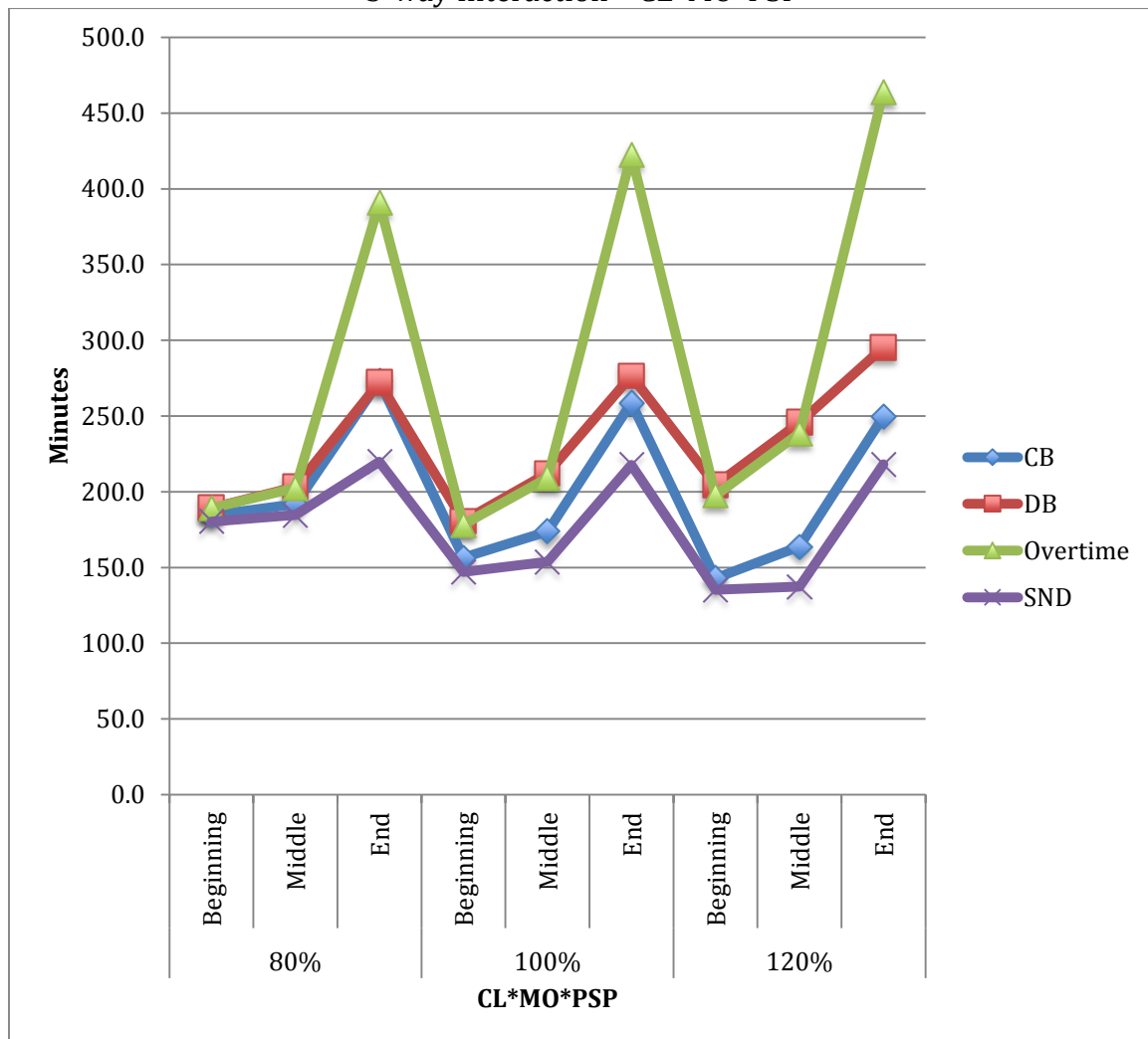


6.7 CL*MO*PSP

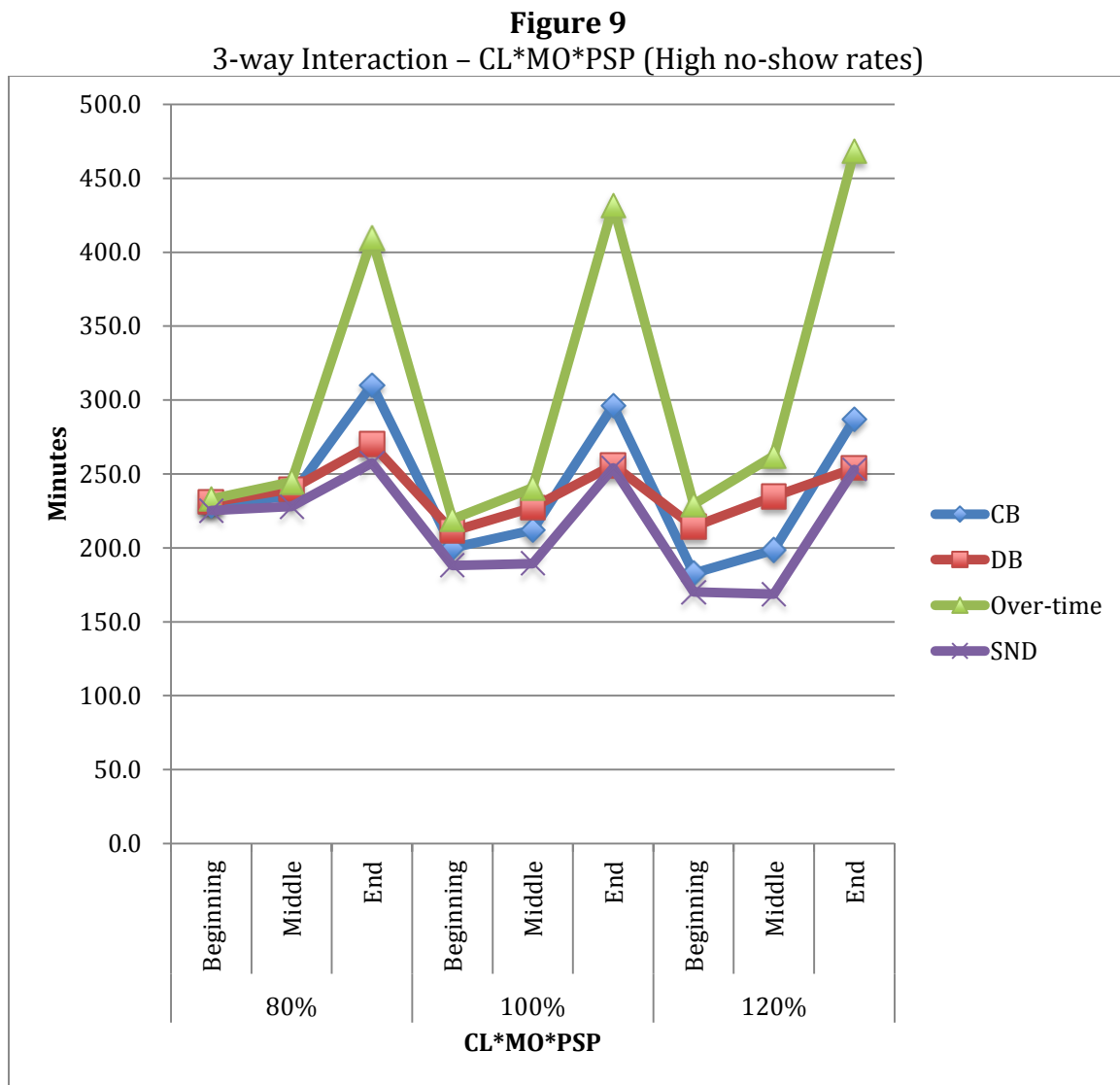
Figure 8 shows the 3-way interaction between CL, MO and PSP, just for the main performance measure. This 3-way interaction analysis further reinforces all the above analyses. As mentioned earlier, Beginning is still the best way to place pre-booked slots regardless of the levels of CL and MO and thus it is these results that are focused on. SND and CB are still the two best rules regardless of the levels of the other factors. SND is always slightly better than CB due to its low idle time. This result

shows that a 2-day booking window performs better than the same-day access policy, which is in line with what has been found by Robinson and Chen (2009). However, recall that SND may result in some not being scheduled after a one-month period when the demand is higher than usual. Thus, this rule should only be used when the system is either 80% or 100% loaded.

Figure 8
3-way Interaction – CL*MO*PSP



With a 120% load, Overtime is the best rule for clinics. As mentioned earlier, the lower WT has been the reason why Overtime could outperform DB in certain scenarios.



Finally, based on the above analysis, 100% load is still the most ideal scenario for open access clinics. This has shown that a balance between demand and capacity is critical for open access clinics. Note that there will be a change in the results when

the cost of idle time is weighted more – using Overtime in an overloaded system results in slightly better performance due to the lower idle time.

Some changes in the results with high no-show rates are revealed in Figure 9. When the no-show rates are high, DB always outperforms Overtime due to its low idle time and over time and it also outperforms CB with an End policy, which suggests that the best rule to use for an overloaded system is DB when the no-show rates are high.

7. Conclusions and Managerial Implications

Since the data was collected from an open access family healthcare clinic, conclusions and implications apply best to similar environments. First of all, it is obvious that pre-booked slots placement is of great importance for open access clinics since it counted for a large amount of variation in the ANOVA test. This study shows that placing pre-booked slots at the beginning of each day is the best option for open access clinics to use. This is also in line with what Herriott (1999) has suggested. Open access should use this suggestion at all times due to its large impact on clinical performance. All the following implications are also made based on this suggestion.

Secondly, it has been revealed that SND is the best rule when the system is either 80% loaded or 100% loaded. This, in a way, shows that a 2-day booking window is advantageous over the same-day access policy, which is the same as what has been discovered by Robinson and Chen (2009). In this model, Monday is the day where the demand is the higher than the capacity while Wednesday and Thursday's demand is lower than the capacity. Thus, SND helps the clinic reduce some pressure

on Mondays by scheduling the excessive patients into Wednesdays and Thursdays. This not only reduces the clinic overtime and patient waiting time on Mondays but also reduces doctor idle time on Wednesdays and Thursdays. However, in reality, different clinics may have different demand patterns. This policy should also be able to help them improve their performance as long as their demand is not always higher than the capacity. With higher than usual demand, SND will result in a few patients who cannot be scheduled after a one-month period. In this case, clinics should consider using Overtime when no-show rates are low and using DB when no-show rates are high. Although the analysis has shown that CB is also a good policy for open access clinics to use, this option is not recommended for two reasons. First, some patient callbacks are left out of the model in this study due to the lack of information on the time and probability of callbacks. Second, by simply asking patients to call back, patient satisfaction and service quality cannot be guaranteed, and clinic income is reduced if they do not call back. Note that for clinics that consider doctor idle time much more costly than patient waiting time, CB should never be used since it is one of the two rules that generates the most idle time.

Finally, the analysis shows that a 100% load will result in the best performance for open access clinics, which shows that a proper panel size is critical for open access clinics. Although the analysis shows that SND and CB perform the best with 120% load, these two rules are not recommended in an overloaded system since they lead to many patients not being scheduled. This study suggests that the best rule for an overloaded system depends on the actual no-show rates. With low no-show rates for both pre-booked and open access patients, the best rule to use is Overtime;

with high no-show rates, however, the best rule to use is DB. Open access clinics should also make contingency plans to deal with any change in demand. After determining the right number of open access slots, clinics should be able to adjust their scheduling rules based on different demand levels and different no-show rates. Again, for clinics where doctor idle time is at least ten times as costly as patient waiting time, a higher than usual demand actually leads to slightly better performance when Overtime is used. Thus, reducing doctor idle time is the first priority for these clinics.

8. Limitations and Future Research

This research adds to the previous literature in a few ways. Firstly, to the best of the author's knowledge, it is the first study aiming to improve performance in open access clinics – prior studies usually compared open access and traditional scheduling systems. Second, this study used variable doctor service time. Third, it used variable daily demand in an open access environment. Finally, a number of decision factors were used to find ways to improve performance in open access clinics.

However, this study still has some limitations that could be improved by future research. In this study, a single server model was built and it was assumed that doctors within the same health care team do not share patients. In reality, clinics schedule patients with doctors who are not their primary physicians. This may hurt the continuity of care but it could be another way for clinics to deal with excessive demand. Future research could include more than one server in the model to examine the effect of health care teams in open access clinics.

The amount of data collected in this study is limited. In order to model a multi-server environment, demand data (call arrival time) would need to be collected for each doctor in the clinic and on each day of a week to establish a demand pattern for each doctor over a certain amount of time. Future research could collect more data to get more accurate demand pattern for open access clinics, build more realistic models and get more reliable results.

Although patient callbacks are, to some extent, reflected in the data, some of the callbacks were still left out when the CB policy was modeled due to the complex behavior of patients. Future studies could measure callbacks more accurately by determining the percentages of patients who actually call back and the time when they call back. This could help researchers build more realistic models and examine the effect of CB more accurately.

Although this study has modeled some uncertainties and decision factors, future studies could include more factors and more uncertainties such as patient punctuality, doctor punctuality and more scheduling rules to provide more managerial implications for open access clinics.

REFERENCES

- Belardi, F. G., Weir, S., & Craig, F. W. (2004). A controlled trial of an advanced access appointment system in a residency family medicine center. *FAMILY MEDICINE-KANSAS CITY*, 36(5), 341-345.
- Bennett, K. J., & Baxley, E. G. (2009). The effect of a carve-out advanced access scheduling system on no-show rates. *Family medicine*, 41(1), 51.
- Bundy, D. G., Randolph, G. D., Murray, M., Anderson, J., & Margolis, P. A. (2005). Open access in primary care: results of a North Carolina pilot project. *Pediatrics*, 116(1), 82-87.
- Carlson, B. (2002). Same-day appointments promise increased productivity. *Managed Care*.
- Chung, M. K. (2002). Tuning up your patient schedule. *Family practice management*, 9(1), 41-45.
- DeLaurentis, P., Kopach, R., Rardin, R., Lawley, M., Muthuraman, K., Wan, H., Intrevado, P. (2006). Open access appointment scheduling-an experience at A community clinic. *IIE Annual Conference. Proceedings*, 1-6.
- Denton, B., & Gupta, D. (2003). A sequential bounding approach for optimal appointment scheduling. *Iie Transactions*, 35(11), 1003-1016.
- Gopalakrishna, P., & Munnalneni, V. (1993). Influencing satisfaction for dental services. *Journal of health care marketing*, 13(1), 16.
- Green, L. V., Savin, S., & Murray, M. (2007). Providing timely access to care: what is the right patient panel size? *Joint Commission Journal on Quality and Patient Safety*, 33(4), 211-218.
- Herriott, S. (1999). Reducing delays and waiting times with open-office scheduling. *Family practice management*, 6, 38-43.
- Ho, C. J., & Lau, H. S. (1992). Minimizing total cost in scheduling outpatient appointments. *Management science*, 38(12), 1750-1764.
- Ho, C. J., & Lau, H. S. (1999). Evaluating the impact of operating conditions on the performance of appointment scheduling rules in service systems. *European Journal of Operational Research*, 112(3), 542-553.
- Kennedy, J. G., & Hsu, J. T. (2003). Implementation of an open access scheduling system in a residency training program. *Family Medicine*, 35(9), 666-670.

- Kilo, C. M., & Endsley, S. (2000). As good as it could get: remaking the medical practice. *Family practice management*, 7(5), 48-52.
- Klassen, K. J., & Rohleder, T. R. (1996). Scheduling outpatient appointments in a dynamic environment. *Journal of Operations Management*, 14(2), 83-101.
- Klassen, K. J., & Rohleder, T. R. (2004). Outpatient appointment scheduling with urgent clients in a dynamic, multi-period environment. *International Journal of Service Industry Management*, 15(2), 167-186.
- Knight, A. W., Padgett, J., George, B., & Dato, M. R. (2005). Reduced waiting times for the GP: two examples of "advanced access" in Australia. *Medical Journal of Australia*, 183(2), 101.
- Kolata, G. (2001). Harried Doctors Try to Ease Big Delays and Rushed Visits. *The New York Times*.
- Kopach, R., Po-Ching DeLaurentis, Lawley, M., Muthuraman, K., Ozsen, L., Rardin, R., Willis, D. (2007). Effects of clinical characteristics on successful open access scheduling. *Health Care Management Science*, 10(2), 111-24.
- Liu, L., & Liu, X. (1998). Block appointment systems for outpatient clinics with multiple doctors. *Journal of the Operational Research Society*, 49(12), 1254-1259.
- Murray, M., & Tantau, C. (1999). Redefining open access to primary care. *Managed Care Quarterly*, 7, 45-55.
- Murray, M., & Tantau, C. (2000). Same-day appointments: Exploding the access paradigm. *Family Practice Management*, 7(8), 45-50.
- Murray, M., Bodenheimer, T., Rittenhouse, D., & Grumbach, K. (2003). Improving timely access to primary care. *JAMA: the journal of the American Medical Association*, 289(8), 1042-1046.
- Murray, M., & Berwick, D. M. (2003). Advanced access. *JAMA: the journal of the American Medical Association*, 289(8), 1035-1040.
- Mehrotra, A., Keehl-Markowitz, L., & Ayanian, J. Z. (2008). Implementing open-access scheduling of visits in primary care practices: A cautionary tale. *Annals of Internal Medicine*, 148(12), 915-922.
- O'Connor, M. E., Matthews, B. S., & Gao, D. (2006). Effect of open access scheduling on missed appointments, immunizations, and continuity of care for infant well-child care visits. *Archives of pediatrics & adolescent medicine*, 160(9), 889.
- O'Hare, C. D., & Corlett, J. (2004). The outcomes of open-access scheduling. *Fam Pract Manag*, 11(2), 35-8.

- Parente, D. H., Pinto, M. B., & Barber, J. C. (2005). A pre-post comparison of service operational efficiency and patient satisfaction under open access scheduling. *Health care management review, 30*(3), 220-228.
- Patrick, J. (2012). A Markov decision model for determining optimal outpatient scheduling. *Health care management science, 15*(2), 91-102.
- Pierdon, S., Charles, T., McKinley, K., & Myers, L. (2004). Implementing advanced access in a group practice network. *Family practice management, 11*(5), 35.
- Qu, X., Rardin, R. L., Williams, J. A. S., & Willis, D. R. (2007). Matching daily healthcare provider capacity to demand in advanced access scheduling systems. *European Journal of Operational Research, 183*(2), 812-826.
- Randolph, G. D., Murray, M., Swanson, J. A., & Margolis, P. A. (2004). Behind schedule: improving access to care for children one practice at a time. *Pediatrics, 113*(3), e230-e237.
- Robinson, L. W., & Chen, R. R. (2009). A comparison of traditional and open-access policies for appointment scheduling. *Manufacturing & Service Operations Management, 12*(2), 330-346.
- Rohleder, T. R., & Klassen, K. J. (2002). Rolling horizon appointment scheduling: a simulation study. *Health care management science, 5*(3), 201-209.
- Schall, M. W., Duffy, T., Krishnamurthy, A., Levesque, O., Mehta, P., Murray, M., & Sanderson, J. (2004). Improving patient access to the Veterans Health Administration's primary care and specialty clinics. *Joint Commission Journal on Quality and Patient Safety, 30*(8), 415-423.
- Soriano, A. (1966). Comparison of two scheduling systems. *Operations Research, 14*(3), 388-397.
- Sperl-Hillen, J. M., Solberg, L. I., Hroschowski, M. C., Crain, A. L., Engebretson, K. I., & O'Connor, P. J. (2008). Peer Reviewed: The Effect of Advanced Access Implementation on Quality of Diabetes Care. *Preventing chronic disease, 5*(1).
- Steinbauer, J. R., Korell, K., Erdin, J., & Spann, S. J. (2006). Implementing open-access scheduling in an academic practice. *Family practice management, 13*(3), 59.

Appendix

ANOVA Post Hoc tests

Client Load

Multiple Comparisons

Dependent Variable: Performance Measurement

Tukey HSD

(I) Client Load	(J) Client Load	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
100%	80%	-7.953*	.2063	.000	-8.436	-7.469
	120%	-8.787*	.2063	.000	-9.271	-8.304
80%	100%	7.953*	.2063	.000	7.469	8.436
	120%	-.835*	.2063	.000	-1.318	-.351
120%	100%	8.787*	.2063	.000	8.304	9.271
	80%	.835*	.2063	.000	.351	1.318

Based on observed means.

The error term is Mean Square (Error) = 25.529.

*. The mean difference is significant at the 0

Homogeneous Subsets

Performance Measurement

Tukey HSD^{a,b}

Client Load	N	Subset		
		1	2	3
100%	1200	215.586		
80%	1200		223.539	
120%	1200			224.373
Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square (Error) = 25.529.

a. Uses Harmonic Mean Sample Size = 1200.000.

b. Alpha = 0

Management Options for Excessive Demand

Multiple Comparisons

Dependent Variable: Performance Measurement

Tukey HSD

(I) Management Options	(J) Management Options	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
CB	DB	-31.700*	.2382	.000	-32.312	-31.087
	Overtime	-77.423*	.2382	.000	-78.036	-76.811
	SND	22.001*	.2382	.000	21.388	22.613
DB	CB	31.700*	.2382	.000	31.087	32.312
	Overtime	-45.724*	.2382	.000	-46.336	-45.112
	SND	53.700*	.2382	.000	53.088	54.312
Overtime	CB	77.423*	.2382	.000	76.811	78.036
	DB	45.724*	.2382	.000	45.112	46.336
	SND	99.424*	.2382	.000	98.812	100.036
SND	CB	-22.001*	.2382	.000	-22.613	-21.388
	DB	-53.700*	.2382	.000	-54.312	-53.088
	Overtime	-99.424*	.2382	.000	-100.036	-98.812

Based on observed means.

The error term is Mean Square (Error) = 25.529.

*. The mean difference is significant at the 0

Homogeneous Subsets

Performance Measurement

Tukey HSD^{a,b}

Management Options	N	Subset			
		1	2	3	4
SND	900	177.385			
CB	900		199.385		
DB	900			231.085	
Overtime	900				276.809
Sig.		1.000	1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square (Error) = 25.529.

a. Uses Harmonic Mean Sample Size = 900.000.

b. Alpha = 0

Pre-booked Slots Placement

Multiple Comparisons

Dependent Variable: Performance Measurement

Tukey HSD

(I) Pre-booked Slots Placement	(J) Pre-booked Slots Placement	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Beginning	End	-122.708*	.2063	.000	-122.225	123.192
	Middle	-19.169*	.2063	.000	-19.652	-18.685
End	Beginning	122.708*	.2063	.000	122.225	123.192
	Middle	103.540*	.2063	.000	103.056	104.023
Middle	Beginning	19.169*	.2063	.000	18.685	19.652
	End	-103.540*	.2063	.000	-103.056	104.023

Based on observed means.

The error term is Mean Square (Error) = 25.529.

*. The mean difference is significant at the 0

Homogeneous Subsets

Performance Measurement

Tukey HSD^{a,b}

Pre-booked Slots Placement	N	Subset		
		1	2	3
Beginning	1200	173.874		
Middle	1200		193.042	
End	1200			296.582
Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square (Error) = 25.529.

a. Uses Harmonic Mean Sample Size = 1200.000.

b. Alpha = 0